

CONSUMER RETURNS IN RETAILING

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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May 2016

Major Subject: Information & Operations Management

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ABSTRACT

In this dissertation, I develop econometric and optimization models to help retailers better manage their consumer returns. I shed light on some prevalent industry practices and beliefs relevant to consumer returns management and provide managerial implications while filling some of the existing gaps in the literature of consumer returns. In the first essay, I examine the association between in-store customer shopping experience during a purchase and subsequent return and repurchase behavior. Using over 21 million purchase and return transactions and nearly 75,000 customer satisfaction survey responses from a national jewelry retailer, I conduct a detailed analysis that incorporates a sample selection model with simultaneous recursive equation models. Return rates across stores within the same company can vary significantly. In the first part of this essay, I empirically examine this variation with respect to product quality, service quality, and customer satisfaction. The analysis reveals surprising findings for retailers. For instance, I demonstrate that retail efforts such as increasing salesperson competence and improving store environment, so long believed to reduce returns, may actually be associated with increased returns. I also show that service quality during a purchase can be more important than product quality in return prevention. In the second part of this essay, I provide empirical evidence that a return event can moderate the satisfaction-repurchase behavior link. More importantly, I show that that a return event may enable a retailer to regain a dissatisfied customer who would otherwise be lost.

In the second essay, motivated by common practice, I study the retail strategy of selling open-box returns side-by-side with new products. I develop a model to assess the impact of cannibalization due to open-box product sales on profitability and to identify the conditions in which selling them is preferred to simply salvaging them through liquidators. The operational decisions are the order quantity, the refund amount, and the open-box product price. The model captures important market characteristics that include consumer choice between

new and open-box products, uncertainty and heterogeneity in consumer valuation for both products, and customer sensitivity to a retailer's return policy. I find that, even if open-box products cannibalize new demand, selling returns as open-box is always more profitable than simply salvaging them so long as there is demand for open-box products. Furthermore, retailers may increase their market share by selling open-box products if customer sensitivity to a retailer's return policy is low. If it is high, retailers should use a generous policy while charging premium prices. I also demonstrate that higher return rates do not necessarily lead to a decrease in profit.

DEDICATION

Dedicated to my dear wife Larisa, precious daughter Alina, my mother Gunseli, and my father Nadi who passed away in 2008 yet, I certainly believe, is watching me over the skies...

ACKNOWLEDGEMENTS

I would never have been able to finish my dissertation without the guidance of my committee members, help from faculty members/friends, and support from my family.

I would like to express my deepest gratitude to my advisor Dr. Michael Ketzenberg, for his excellent guidance, caring, patience, and encouragement along my Ph.D. program. I have learned a lot from him not only in developing skills as an academic, but also about how to be a great mentor to make a positive significant change in others' life. Outside the academic life, I had very difficult moments that were enough to discourage any Ph.D. student to continue in the program. His sincere and continuous support during those moments helped me overcome any difficulty I had. I hope I can have the chance to give back to the community in the future by being a great advisor and a great mentor like Dr. Michael Ketzenberg.

I wish to thank Dr. Gregory Heim first, for his guidance through several matters during my doctoral program and second, for his service as a member in my committee. He is certainly a great co-author to work with. I would like to thank the rest of my committee: Dr. Chelliah Sriskandarajah and Dr. Haipeng "Allan" Chen for their insightful and constructive comments on my dissertation.

I want to send my special thanks to Dr. Rich Metters for his excellent leadership as the Department Chair, his efforts to provide sources to improve the quality and skills of doctoral students, and his motivation to make the life for doctoral students more enjoyable. I also want to thank Dr. Neil Geismar, Dr. Rogelio Oliva, Dr. Subodha Kumar, Dr. James Abbey, Ms. Donna Shumaker, Ms. Tammy Louthier, and the rest of the department for the help I got so freely from them whenever I needed. Another special thanks to all doctoral students at the department for being caring and encouraging friends.

Lastly, I cannot find a word to express my deep gratitude to my parents who have taught me honesty, respect for others, and dignity. I know they are always with me and never let me feel alone. I send my most special thanks to my wife and daughter for their never ending

support. They are at the center of my life and main motivation for me to try my best to be successful in this life.

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1. INTRODUCTION AND MOTIVATION

The 2013 National Retailer Federation Annual Returns Survey report indicates that total merchandise returns account for almost \$270 billion in lost sales for U.S. retailers. To emphasize the overwhelming size of returns, the report makes the analogy that “if merchandise returns were a company it would rank #3 on the Fortune 500” (NRF, 2013). What do we know about consumer returns? We know that returns have been growing consistently, if not inordinately, with an overall increase of 41.5% since 2007 (NRF, 2007, 2013). We also know that they are costly for companies. On average, returns reduce manufacturers’ and retailers’ profits by 4% to 6% (Richardson, 2004; Douthit et al., 2011) and force them to incur additional operational costs such as shipping and handling that may amount to as much as \$14 billion (Lawton, 2008).

Consumer returns are not new. Indeed, they have been an endemic part of business since Montgomery Ward & Co., the world’s first mail-order retail company, adopted the innovative and unprecedented policy of “satisfaction guaranteed or your money back” in 1875 (Brennan, 1991). In a survey of supply chain managers, 87% respond that they are aware of the importance of consumer returns and agree that managing returns effectively is important to achieve operational and financial success (Aberdeen, 2009 (accessed February 13, 2014)). How do companies manage returns effectively? For that matter, what does *managing returns effectively* really mean?

Some retailers are moving toward stricter return policies including a shorter time period to return or applying a restocking fee in an effort to reduce returns and recoup costs associated with them (Bower and Maxham, 2012; Janakiraman and Ordonez, 2012). Some retailers are trying to prevent returns before they occur by providing a better customer sales experience during and after a purchase (Meyer, 1999; Stock et al., 2006). Others are trying to increase the value they obtain from returns by reselling them along with new products (Consumer-Reports, 2008 (accessed Jun 27, 2014)).

Despite the size and importance of returns, research remains limited. For instance, we do know from the literature that return rates vary across industries and firms (Rogers and Tibben-Lembke, 1998) largely due to differences in product categories, return policies, and customer bases. Such variation can also be present in a single company across multiple stores. But why? What are the attributes that drive these varying behaviors? The literature assumes that retailers may prevent returns by improving the customer sales experience, driving more informed purchases, and providing better post-sale support (Douthitt et al., 2011; Ofek et al., 2011). Unfortunately, there are no studies that address the efficacy of these prescriptions. While practitioners mainly focus on return prevention (Anonymous, 2015 (accessed Apr 01, 2015), there is anecdotal evidence in the literature that suggests returns might be another opportunity to enhance customer relationships (Petersen and Kumar, 2009; Griffis et al., 2012). Should retailers prevent returns or leverage them to build a better customer relationship? Even if returns enable retailers to enhance customer relationships for future business, does that mean that retailers do not need to worry about the disposition of returns? Are there smart ways to dispose of returns that will increase the value obtained from them?

The questions that motivate this dissertation address some prevalent industry practices and beliefs with respect to effective returns management. In this dissertation, I use a holistic approach to shed light on these and similar questions. I believe that effective returns management is encapsulated within a continuum that spans multiple operations and customer services from the initial design of a product to the disposition of a returned product. In particular, effective returns management should include (1) designing and manufacturing high quality products that have easy setup and installation for customers, (2) delivering high quality service at the point of purchase to ensure the right match with customer preferences, (3) providing after-sale customer support when needed, (4) offering a return policy that reduces the risk of mismatch for legitimate customers while minimizing costs due to opportunistic customers, (5) facilitating returns to ensure customer satisfaction and leveraging them to enhance customer relationships, and (6) disposing returns efficiently. From this perspective,

this dissertation focuses on (1) the in-store shopping experience during a purchase, (2) monitoring and influencing customer satisfaction during a return process, and (3) effective and efficient disposition methods for returned products. This dissertation provides managerial insights while filling some of the existing gaps in the literature on consumer returns. In particular, it comprises two essays in which I develop econometric and optimization models to help retailers better manage consumer returns.

In the first essay, I study returns at a national jewelry retailer, hereafter called Diamond. I examine the association between in-store customer shopping experience during a purchase and subsequent return and repurchase behavior. Using over 21 million purchase and return transactions and nearly 75,000 customer satisfaction survey responses from Diamond, I conduct a detailed analysis that incorporates a sample selection model with simultaneous recursive equation models. I demonstrate that return rates across stores within the same company can vary significantly. In the first part of this essay, I empirically examine this variation with respect to product quality, service quality, and customer satisfaction. The analysis reveals surprising findings for retailers. For instance, I demonstrate that retail efforts such as increasing salesperson competence and improving store environment, so long-believed to reduce returns, may actually increase returns. I also show that service quality during a purchase can be more important than product quality in return prevention. In the second part of this essay, I provide empirical evidence that a return event can moderate the satisfaction-repurchase behavior link. More importantly, I show that a return event may enable a retailer to regain a dissatisfied customer who would otherwise be lost.

The first essay provides several useful managerial insights pertaining to return prevention and returns processing and is likely to help managers to reduce returns. Even so, retailers will always have to handle returns as long as they allow them. As such, retailers need to effectively and efficiently manage their disposition. There are a variety of methods including sending returned products back to the manufacturer for credit, selling them to third party liquidators at a deep discount, and selling them side-by-side with their new products at a discounted price. Interestingly, selling side-by-side with new products has not garnered much attention

from researchers. Even though this strategy is common in practice, it remains unclear how such a retail strategy should be tactically implemented. The second essay addresses this gap in the literature.

In the second essay, I develop a model to assess the impact of cannibalization due to open-box product sales on profitability and to identify the conditions in which selling them side-by-side with new products is preferred to simply salvaging them through liquidators. The model captures important market characteristics that include consumer choice between new and open-box products, uncertainty and heterogeneity in consumer valuation for both products, and customer sensitivity to a retailer's return policy. I determine several operational decisions including the order quantity, the refund amount, and the open-box product price since these are the key levers that affect a firm's ability to operationally match supply with demand. I find that, even if open-box products cannibalize new demand, selling returns as open-box is always more profitable than simply salvaging them so long as there is demand for open-box products. Furthermore, retailers may increase their market share by selling open-box products if customer sensitivity to a retailer's return policy is low. If it is high, retailers should use a generous policy while charging premium prices. I also demonstrate that higher return rates do not necessarily lead to a decrease in profit.

The rest of this dissertation is organized as follows. In Chapter 2, I introduce the first study that identifies the key drivers of returns and assesses the impact of a return event on customer relationship. This is followed by the second essay in Chapter 3 in which, I introduce a return policy for a retailer that resells returned products at a discounted price. Finally, Chapter 4 concludes my dissertation with a discussion about the contribution of this dissertation to the academic literature and to practice.

2. THE RELATIONSHIP BETWEEN IN-STORE SHOPPING EXPERIENCE, CONSUMER RETURNS, AND REPURCHASE BEHAVIOR? AN EMPIRICAL STUDY

2.1 Introduction

The annual value of consumer returns in the U.S. reached \$284 billion in 2014, an increase of 50.3% since 2007 (NRF, 2007, 2014). For managers, it is not just problematic that returns are significant and increasing, but that they are costly too. Product returns can reduce profits on average by 5% to 6% for manufacturers (Douthitt et al., 2011) and by 4% for retailers (Richardson, 2004). Clearly, effective management of returns provides an opportunity to increase supplier and retailer profitability.

Many factors drive product returns including defects, trade-ins, end-of-life returns, opportunism, and fraud. Other significant reasons include buyer's remorse and product mismatch with customer preference. I focus on the association between in-store customer experience and subsequent returns, which may be a consequence of buyer's remorse or a mismatch. These types of returns account for a large portion of all returns. For example, they are 80% of all returns in HP's inkjet printer group (Ferguson et al., 2006) and 95% of all returns across all consumer electronics (Douthitt et al., 2011). In comparison, note that only 5% of all consumer returns were reported to be truly defective (Lawton, 2008).

The types of returns I study arise due to product valuation uncertainty (Su, 2009). Prior to a purchase, customers have an expectation about the value of a product. Once a product is used and experienced, customers are able to realize their perceived valuation. If the perceived valuation is substantially less than the expected valuation, perhaps due to poor quality or a mismatch in taste, customers may be dissatisfied (Kotler, 1991). Retailers offer return policies to insure customers against the risk of potential dissatisfaction. While lenient return policies are likely to increase sales (Ketzenberg and Zuidwijk, 2009; Akcay et al., 2013), they will also generate costly returns.

Given the significance of returns, companies often invest substantially to manage returns effectively. Yet, firms generally do so reactively, after returns occur (Aberdeen, 2009 (accessed February 13, 2014)). The main focus of reactive approaches is on how best to handle and dispose of the returns once they arise. In contrast, as suggested by a consumer electronics industry report by Accenture (Douthit et al., 2011), I believe that effective returns management should also involve proactive approaches to monitor and influence customer satisfaction at the point of purchase and to set appropriate expectations. Proactive approaches to ensure satisfaction and product match during a purchase event should prevent returns from occurring. Indeed, managers today are actively interested in return prevention. An annual “Consumer Returns” conference for retailers highlights the importance of several proactive approaches to improve the customer sales experience (Anonymous, 2015 (accessed Apr 01, 2015)). Such approaches may include both product and service aspects of the sales experience. On the product side, thought leaders recommend offering high quality products, increasing product variety, and improving product displays. On the service side, recommended tactics include hiring qualified salespeople, training employees, driving more informed purchases, and changing the store environment (Douthit et al., 2011). A few studies assume certain tactics work and develop analytical models to address returns within the context of supply chain issues including coordination between a manufacturer and a retailer (Ferguson et al., 2006) and store assistance levels for dual channel retailers (Ofek et al., 2011). However, I am not aware of any empirical study that addresses the efficacy of return prevention factors. It is not clear how much, if any, each of the suggested practices influences returns.

Clearly, proactive approaches to manage returns can be irrelevant for some products, particularly for repeated purchases of products for which customers are already familiar. Considering that products can be categorized as convenience goods (e.g. groceries, office supplies, personal care), shopping goods (e.g. apparel, sunglasses, jewelry), and specialty goods (e.g. computers, digital cameras, video game consoles) (Thirumalai and Sinha, 2005), returns due to product mismatch will most likely occur in shopping and specialty goods

due to the lack of familiarity. In this research, I study the return behavior for high fashion products that are examples of shopping goods. Specifically, I study jewelry purchases and returns at a national jewelry retailer, hereafter called Diamond. Since a significant amount of jewelry purchases are gifts, providing customer service to identify the gift recipient’s taste is extremely important for Diamond. Indeed, returns due to product mismatch with customer preference constitute 81% of all returns at Diamond. With average returns of approximately 18% of sales, jewelry returns are significant and most returned items are in perfect working condition, also known as “good as new” in the literature (Mostard and Teunter, 2006).

What is remarkable and equally stunning to Diamond management is the substantial variation in return rates across stores. Figure 2.1(a) indicates the annual return rate as a percentage of USD revenue for 1,167 Diamond stores in 2012, ordered from lowest to highest and ranging from 7% to 47%. Prior literature draws attention to varying return rates across industries (Rogers and Tibben-Lembke, 1998), demonstrating sector-specific return rates from 4% to 35% (Douthit et al., 2011; Rogers and Tibben-Lembke, 1998) and proposing the variance arises from differences in product categories, return policies, and customer bases. Yet, no study explain why return rates can vary significantly across stores within the same company, wherein differences in products, return policies, and customer bases do not exist. I contribute by examining potential explanations for this variation.

Clearly, other factors drive the level and variation in returns across stores. One potential explanation is store labor. Figure 2.1(b) demonstrates annual return rates as a percentage of USD sales for 9,120 salespeople in all stores during 2012, again ordered from lowest to highest and ranging from 4% to 54%. This picture demonstrates wide variation in individual salesperson return rates. The skills and effectiveness of salespeople vary and so do their individual return rates. Intuitively, one may expect that salespeople who are better able to satisfy customer needs should demonstrate lower return rates. Further, with a single corporate delivery policy, one might expect the quality of the sales force to be distributed fairly evenly throughout the company’s stores. Yet, when I take a further look at return rates of salespeople grouped within stores (Figure 2.1(c)), I observe that low (high) performing

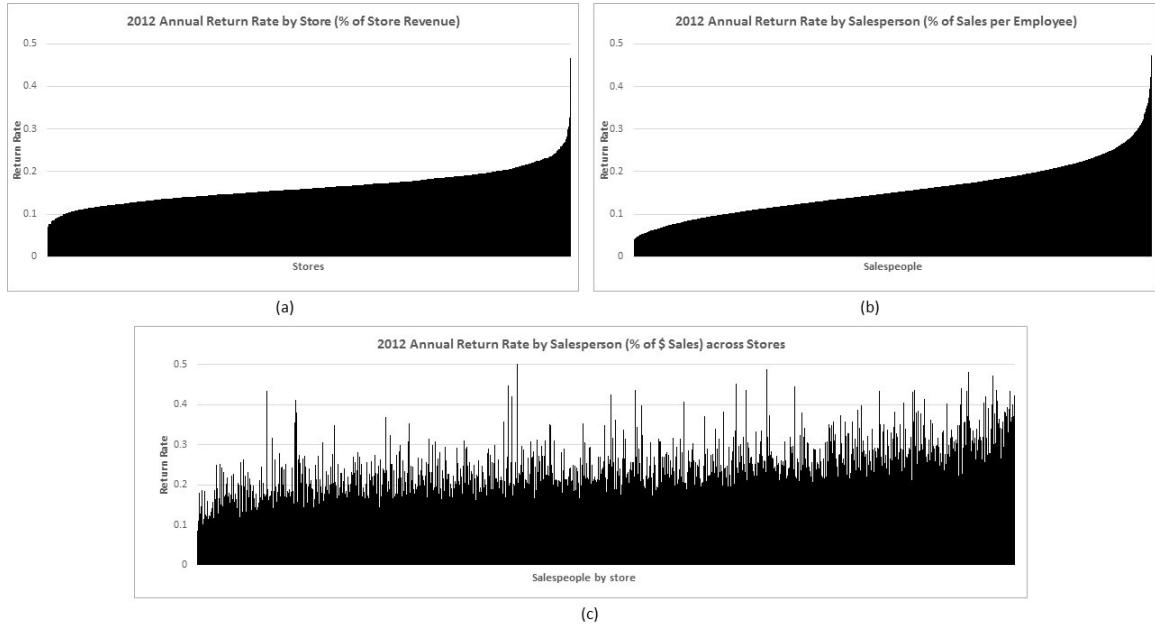


Figure 2.1: Diamond 2012 annual return rates by stores and by salespeople

stores have low (high) performing salespeople (the right (left) side of Figure 2.1(c)), indicating a store effect. Return rates obviously vary substantially by store indicating a store effect. Stores with low return rates must have different practices or better store execution than stores with high return rates. Identifying these practices and implementing them across stores may provide significant opportunities for retailers. Consider that even a 1% reduction in the company-wide average return rate corresponds to a \$17 million increase in net sales at Diamond. For the entire U.S. retailing sector, a 1% reduction in the average consumer return rate promises \$31.9 billion in savings (NRF, 2014). But, what are the return prevention practices that would generate such savings? What can store managers do to reduce or otherwise manage returns? Answering these questions is the principle motivation for this study.

I aim to explain the variation in return rates with respect to product quality and service quality at the point of purchase. I do so because these factors have been shown to have a clear influence on customer satisfaction. I also believe proactively managing customer sat-

isfaction at the point of purchase will enable managers to manage returns more effectively. Empirical studies in marketing and closed-loop supply chain literature state that returns can be influenced by price (Anderson et al., 2006), lenient or restricted return policies (Petersen and Kumar, 2009), information provided regarding alternative products before or after a purchase (Bechwati and Siegal, 2005), and online retailer technology (De et al., 2013). However, I am not aware of any empirical research that addresses customer satisfaction, service quality, and product quality as the potential drivers of returns. I contribute by examining the association between in-store customer experience and subsequent return behavior.

Customer return behavior within the context of satisfaction naturally leads to another interesting question. How does a return event moderate the link between satisfaction and repurchase behavior? Repurchase behavior refers to a customer's total future spending and is a strong indication of customer loyalty. Many studies report a positive relationship between customer satisfaction and repurchase behavior (Cooil et al., 2007; Oliver, 2009). However, some studies empirically show that improving customer satisfaction does not always result in an increase in repurchase behavior under certain conditions (Van Doorn and Verhoef, 2008; Voss et al., 2010). I look at this relationship from a consumer returns perspective. Customers perceive a return policy as part of the service package a retailer provides (LoyaltyOne, 2015 (accessed Mar 09, 2015)). Once customers return their products, they will better understand the value offered by a retailer's entire service package. As such, return events provide retailers an opportunity to enhance customer satisfaction and subsequent repurchase behavior since they represent another service point that is valued by customers. Recent consumer surveys suggest customers shop more often at a store if they experience a positive return event (Voxware, 2013 (accessed Mar 09, 2015; LoyaltyOne, 2015 (accessed Mar 09, 2015)). In the academic literature, a few papers examine the impact of returns on repurchase behavior for online retailers (Petersen and Kumar, 2009; Griffis et al., 2012). However, I am not aware of any empirical research that explains how repurchase behavior varies with satisfaction for customers who later experience a return, relative to those who do not return at all in physical stores. I contribute by examining the moderating role of return events in affecting

the relationship between customer satisfaction and repurchase behavior in physical stores.

To answer the research questions, I perform a comprehensive analysis using a unique data set from Diamond. The data consist of around 21 million item-level transactions (of which 19 million are purchase transactions and 2.1 million are return transactions) over a four-year period and around 75,000 customer satisfaction survey responses completed after a purchase event. The data covers every retail outlet of Diamond including over 1,000 stores operating in the U.S. and Canada. Today, regardless of the sector, many major retailers collect similar transaction data and survey data. Therefore, this study contributes managerially by illustrating how managers may make use of such data in their analytics programs.

The data tie customer perceptions recorded within customer surveys to the *actual return and repurchase behaviors* that are recorded in the transaction data. By using this data, I can overcome some of the typical limitations of research based solely on survey data. For example, consumer returns studies that use perceptions measure either return intentions in lab studies with students (Bechwati and Siegal, 2005) or repurchase intentions following a return event through customer surveys (Mollenkopf et al., 2007a). However, these studies lack the ability to represent real market conditions as there is a gap between intentions and actual behavior (Souza, 2013). Similarly, literature that uses only transaction data (e.g. Petersen and Kumar (2009); Griffis et al. (2012)) does not triangulate actual behaviors with customer perceptions regarding a purchase event, and therefore lacks the ability to explain the antecedents of the actual behaviors.

Studies often restrict analysis to only transactions that have corresponding surveys. Such an empirical approach will underutilize data and potentially result in a sample selection problem. To utilize the Diamond data to the maximum extent and to address sample selection, I adapt methodology from the econometrics literature. I use a full information maximum likelihood (FIML) approach to estimate a treatment-effect model.

Overall, I find that retailers can prevent returns from occurring by influencing customer satisfaction during a purchase event through ensuring high service quality and product qual-

ity. I demonstrate that service quality may have even greater influence than product quality on return prevention. I summarize the findings as follows: First, in contrast to the common belief in consumer returns literature that competent salespeople should reduce returns (Ferguson et al., 2006; Ofek et al., 2011), I find that high salesperson competence may be associated with increased returns. This may arise if the information provided by a salesperson unnecessarily increases customer expectations. Second, I show that a pleasant store environment may be associated with increased returns. This also may arise due to setting customer expectations too high since, after a purchase, products do not look or function the way that they do in the store. Third, when customers perceive a product’s quality as low, they are more likely to return the product even if the actual quality may not be low.

With respect to the analysis on repurchase behavior, I find that, on average, a return event increases a customer’s future purchases by \$171 per customer per year. More importantly, the findings suggest that a return event may enable a retailer to regain a dissatisfied customer who would otherwise be lost. I find that the repurchase amount of customers who do not return the products they purchase after a dissatisfactory experience is only \$6. This implies that dissatisfied customers who do not return their initial purchases do not shop with a retail store anymore. Yet, I demonstrate that when these customers return their products, the average repurchase amount increases up to \$154.

I organize the rest of this chapter as follows: In §2.2, I review the relevant literature. In §2.3, I introduce the models and develop hypotheses. In §2.4, I introduce the data set and provide explanations for variables. In §2.5, I explain the methodology. I present the model results in §2.6. Finally, I interpret the findings and conclude the paper in §2.7.

2.2 Prior Literature

This research falls within the product returns literature. This literature is developing in the fields of marketing and closed-loop supply chain management. Even though there have been calls in the literature for empirical research to understand the behavioral nature of product returns (Atasu et al., 2008a), there are still few contributions. The empirical literature on product returns can be categorized into two streams: drivers of return behavior

and customer loyalty with a return experience.

The literature on drivers of return behavior aims to explain factors that give rise to returns. From an assortment perspective, returns tend to occur around a small group of products among all product categories (Rabinovich et al., 2011). However, specific product attributes can be associated with high returns. Hess and Mayhew (1997) and Anderson et al. (2006) observe that consumers are less likely to return lower priced-items. Anderson et al. (2006) also find empirical support for the impact of size and color variety of products on apparel returns. In particular, they show that the number of sizes available is positively associated with returns, whereas increasing color variety is negatively associated with returns. This implies that size variety increases uncertainty whereas color variety leads to a better match.

In e-commerce, customers may not be able to truly evaluate product attributes until they physically receive products. Therefore, providing more information about product fit using e-commerce technology is important. De et al. (2013) show that zoom technology used to enlarge picture of an online product is associated with fewer returns. Alternative photo technology, which shows the product from different views, is also associated with more returns. The authors argue that zoom technology helps to generate expectations close to the true attributes whereas the alternative photo technology leads to too high expectations about the true attributes.

A few papers explain return behavior due to factors such as information availability and shopping characteristics. Bechwati and Siegal (2005) study how consumers' pre-choice thoughts affect the likelihood to return products. They show that when alternative product information (e.g. information about an updated product version or a competitor product having more features) is given to the buyer after a purchase, the likelihood of return is higher than when that information is offered pre-purchase. Petersen and Kumar (2009) demonstrate customers are less likely to return gifts, discounted products, and products purchased in a new sales channel, but more likely to return products purchased during a holiday or purchased from a new category. All studies in this stream highlight important

drivers for consumer returns. I contribute to this stream by explaining variation in return rates across stores and salespeople. In particular, I demonstrate how customer satisfaction, service quality, and product quality drive consumer return behavior.

The literature on customer repurchase behavior in the context of returns is limited. In fact, I am aware of only three studies. Among them, Griffis et al. (2012) show that customers who return items tend to purchase more than those who have never returned. Petersen and Kumar (2009) demonstrate that there is an inverted U-shaped relationship between the amount of products a customer returns and repurchase behavior. Therefore, the amount of returns is positively associated with future customer repurchases up to a threshold level. Bower and Maxham (2012) study the impact of the cost of returns on customer repurchase behavior, showing free returns increase repurchase behavior whereas fee-based returns decrease repurchase behavior. While papers in this stream demonstrate that, in general, a return experience increases customer repurchase, it is not clear whether this finding holds for customers with different satisfaction levels. I contribute to this stream by studying how a return experience moderates the relationship between satisfaction and repurchase behavior.

2.3 Model and Hypotheses Development

I use two models to examine the research questions. The first model focuses on the impact of product quality, service quality, and satisfaction during a purchase event on return behavior. The second model addresses the moderating effect of a return experience on the relationship between customer satisfaction and repurchase behavior.

2.3.1 Key Drivers of Return Behavior at the Point of Purchase

As shown in Figure 2.2, the first structural model proposes that three variables influence customer's return behavior: product quality, service quality, and customer satisfaction. I discuss the relationship between customer satisfaction and return behavior and then introduce the two quality dimensions as determinants of both customer satisfaction and return behavior.

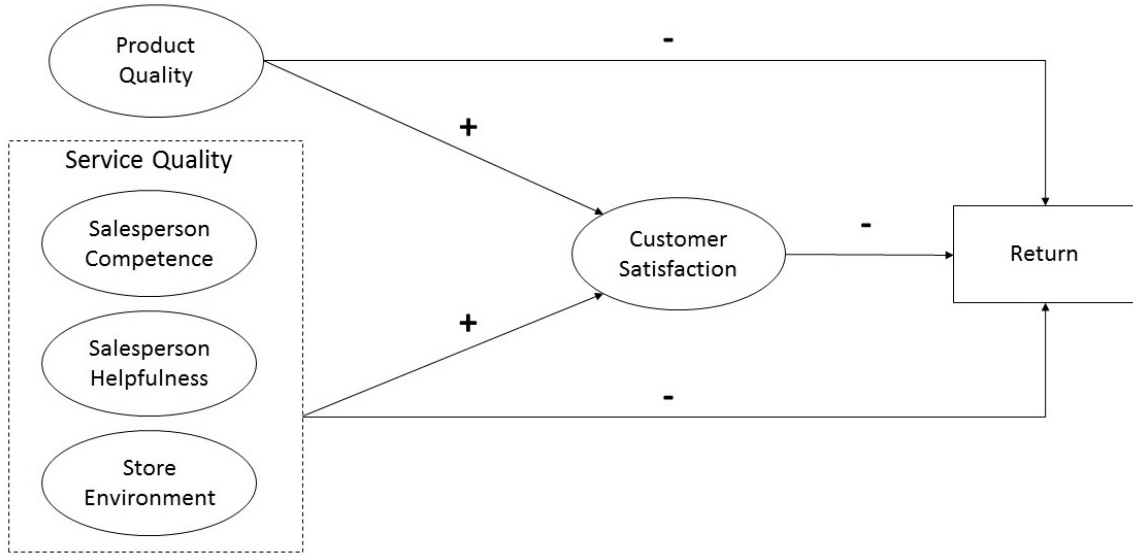


Figure 2.2: Key drivers of returns during a purchase event

2.3.1.1 Customer Satisfaction

In its simplest form, customer satisfaction is characterized as a function of postpurchase perceived valuation (PV) of product quality given prepurchase expected valuation (EV) (Kotler, 1991). When a customer's perceived valuation exceeds his/her expectations ($PV \geq EV$) (falls short of - $PV < EV$), then the customer is satisfied (dissatisfied) (Anderson and Sullivan, 1993).

Assuming valuation can be monetized in the form of willingness-to-pay, the underlying explanation of satisfaction corresponds analogously to that of product returns. Returns occur when a customer's perceived valuation is less than the product price ($PV < \text{Price}$). Moreover, assuming that the salvage value of a returned product is less than its price, retailers set optimal product price to be equal to the expected valuation ($\text{Price} = EV$) since (1) customers will not purchase the product at any price above the expected valuation and (2) retailers lose out on potential revenue for any price they set below the expected valuation (e.g. Che (1996); Su (2009); Akcay et al. (2013)). Therefore, returning a product can be an outcome of a customer's dissatisfaction with that product (Engel et al., 1995; De et al.,

2013). Hence, I hypothesize:

Hypothesis 1 (H1): *Customer satisfaction is negatively associated with returns.*

Research indicates that perceived valuation can be influenced by pre-purchase expectations (Anderson, 1973; Anderson and Sullivan, 1993). In assessing satisfaction with regard to a purchase, customers are likely to consider product features and service features (e.g. empathy, knowledge, and helpfulness of a salesperson) (Parasuraman et al., 1994). Therefore, I will look at two different factors that are likely to influence a customer's perceived valuation: product quality and service quality.

2.3.1.2 Product Quality

Product quality is defined as a customer's appraisal of a product's overall excellence or superiority (Zeithaml, 1988). Many companies consider product quality as one of the driving reasons of returns (Mollenkopf et al., 2007b). Holding other factors constant, high quality products may lead to less frequent returns (Stock et al., 2006; Mukhopadhyay and Setaputra, 2007; Li et al., 2013). Seemingly intuitive, a few modeling papers make this assumption (e.g. Mukhopadhyay and Setaputra (2007); Li et al. (2013)). However, I am not aware of any empirical test of this simple relationship. Hence, I hypothesize:

Hypothesis 2 (H2): *Product quality at the point of purchase is negatively associated with returns.*

A theoretical framework between product quality and satisfaction has been acknowledged by researchers both in the product return literature (Stock et al., 2006; Mukhopadhyay and Setaputra, 2007; Li et al., 2013) and in the marketing literature (e.g. Churchill and Surprenant (1982); Anderson and Sullivan (1993); Parasuraman et al. (1994); Luo and Bhattacharya (2006)). Researchers have consistently shown that product quality is positively associated with satisfaction (e.g. Parasuraman et al. (1994); Oliver (1997, 1999); Baker and Crompton (2000); Devaraj et al. (2001); Olsen (1999); Olsen and Johnson (2003)). I do not formally hypothesize this link since it is not the focus of this study. However, I include it in the theoretical model and estimate it in the analysis.

2.3.1.3 Service Quality

Service quality has been a heavily studied topic over the last 30 years. Service quality is defined as the degree of discrepancy between customers' normative expectations for a service and their perceptions of the service performance (Parasuraman et al., 1985). Service quality and product quality are systemically different due to the service's inherent intangibility, inseparability of production and consumption, heterogeneity, and perishability (Zeithaml et al., 1990). The foundation of service quality theory lies in the product quality and customer satisfaction literature (Brady and Cronin, 2001). Early studies (e.g. Gronroos (1982, 1984); Parasuraman et al. (1985)) conceptualize service quality based on the disconfirmation paradigm. This paradigm suggests that quality results from a comparison of perceived with expected performance.

Following the disconfirmation paradigm, Parasuraman et al. (1985) identify ten determinants of service quality. Subsequently, Parasuraman et al. (1988) develop the SERVQUAL model which recasts the ten determinants into five specific dimensions: reliability, responsiveness, assurance, empathy, and tangibility. Although SERVQUAL instruments have been widely used in many different contexts, several authors have identified potential difficulties with the conceptual foundation and empirical operationalization of the scale (e.g. Carman (1990); Babakus and Mangold (1992); Cronin and Taylor (1992); Teas (1993); Brady and Cronin (2001)). In particular, critics have questioned whether the five dimensions of the scale are generically applicable in all service contexts. Subsequently, adaptations and replacements of SERVQUAL have been suggested for various industry-specific contexts (Carman, 1990).

Retail service quality is the specific context that is relevant to this study. Consistent with prior retail service quality literature (Dabholkar et al., 1996), the author observed during multiple Diamond store visits that the detailed product knowledge that salespeople provide to customers, personality of salespeople (e.g. being helpful and courteous) and physical aspects of stores (e.g. appearance, layout) are different for each store, and may help to explain the variation in return rates across stores and salespeople. Moreover, an individual customer's perceived valuation can be influenced by the content of communications from

salespeople and the context of the store environment (Helson, 1959). Consequently, I address three determinants of service quality: *salesperson competence*, *salesperson helpfulness*, and *store environment*.

Swan et al. (1985) define salesperson competence as the use of technical knowledge and knowledge of customer needs. A customer's perception of salesperson competence plays a critical role in the customer's sales experience and satisfaction (Kennedy et al., 2001; van Dolen et al., 2002). I conjecture that identifying the right product that matches customers' needs requires a salesperson to excel in core tasks and to build empathy with customers to understand their needs. The core tasks of a salesperson include both being knowledgeable about the products and performing tasks specified in the job description, such as following standardized selling orientations (Maxham et al., 2008). To build empathy with customers requires exerting effort towards customers, called extra-role performance (the role of empathy). Such efforts may include getting personally involved with the customer, asking personal questions, and learning the reason for the purchase. Without complete product knowledge and empathy, the risk of a mismatch is likely higher. Overall, salesperson competence allows a salesperson to understand what a customer needs and to provide product information that potentially meets those needs (Beatty et al., 1996). Providing information about a product may reveal a mismatch before purchase and prevent a subsequent return. Yet, a high provision of information may also increase the expectation from a product and increase returns due to diminished postpurchase perceived valuation (Shulman et al., 2015). Therefore, I hypothesize:

Hypothesis 3a (H3a): *Salesperson competence at the point of purchase has a U-shaped association with returns.*

Salesperson helpfulness refers to the interaction of a salesperson with a customer. Salesperson helpfulness can influence a customer's perception about the sales experience (Brown and Lam, 2008). The literature indicates that courteous and friendly employees increase the interest of customers (Baker et al., 1998). Customer interest, in turn, increases not just the time spent in the store but also the willingness to communicate with salespeople

(Donovan and Rossiter, 1982). In addition, when customers are willing to ask questions, it is important to have available assistance. Sharma and Stafford (2000) demonstrate that salesperson availability in a discount store has a significant effect on a customer's buying intention. Timely assistance may help customers to find the right product. Salesperson helpfulness may also lead to variety-seeking through exploring the store, which is likely to increase the probability of finding the right match.

Store environment refers to tangible and intangible aspects of retail store design including interior, exterior, layout, and point of sale (Puccinelli et al., 2009). Retailers strategically plan the store environment including comfortable seats, interior colors, lighting, and well-organized displays and cases to provide a pleasant shopping experience, positively influence customers' purchase behaviors, and ensure that customers find the right match. Overall I hypothesize:

Hypothesis 3b (H3b): *Salesperson helpfulness and store environment at the point of purchase are negatively associated with returns.*

The literature has demonstrated that salesperson competence (Maxham et al., 2008), salesperson helpfulness (Marques et al., 2013), store environment (Becker, 1965; Baker et al., 2002; Buell and Norton, 2011; Marques et al., 2013), and overall service quality (Taylor and Baker, 1996; Spreng and Mackoy, 1996; Ladhari, 2009) lead to satisfaction. As with product quality, I do not formally hypothesize the link between service quality and satisfaction since it is not the purpose of this study. However, I still include it in the theoretical model.

2.3.2 Moderating Role of Return Experience

I finalize the hypothesis development by discussing the moderating effect of a return experience on the relationship between customer satisfaction and repurchase behavior (see Figure 2.3). The academic literature consistently draws a conceptual and empirical link between customer satisfaction and repurchase behavior (Mittal and Kamakura, 2001; Seiders et al., 2005; Bolton and Bramlett, 2006; Cooil et al., 2007; Oliver, 2009). However, recent studies argue that satisfaction has no effect on repurchase behavior under certain circumstances. These studies examine potential moderators for the satisfaction-repurchase behavior rela-

tionship. The moderators include customer and marketplace characteristics (Seiders et al., 2005), relationship duration (Cooil et al., 2007), negative critical incidents (Van Doorn and Verhoef, 2008), and satiation and inertia (Voss et al., 2010). I contribute to this literature by proposing return experience as a moderator variable for the satisfaction-repurchase behavior link.

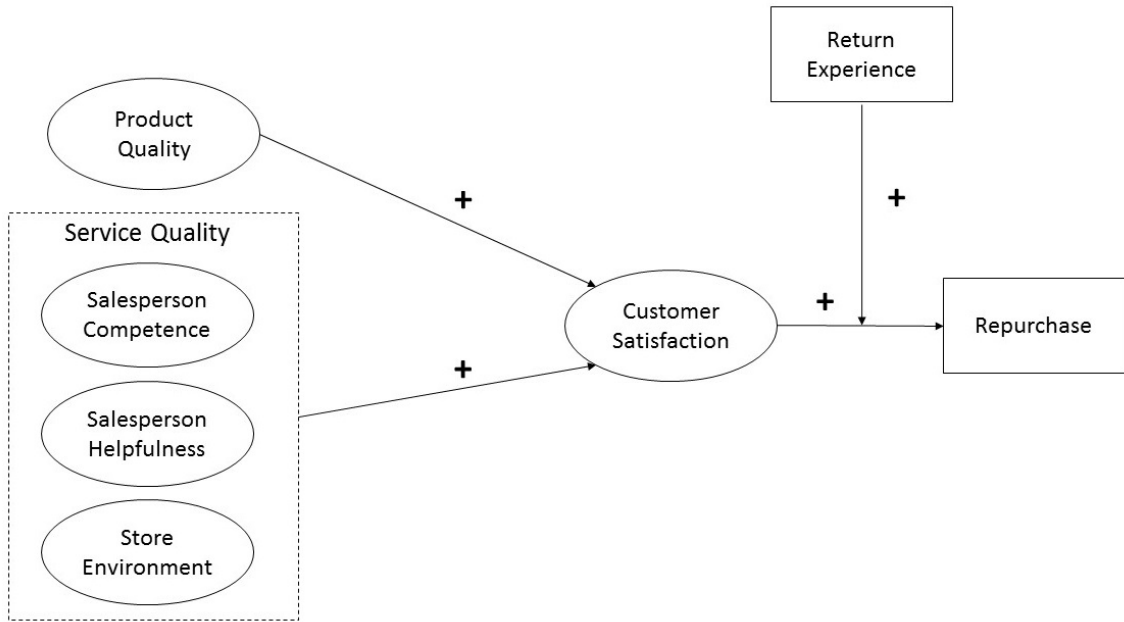


Figure 2.3: Moderating effect of return experience

Return policies are part of the services retailers offer to their customers. As for any particular service point, a return event also provides an opportunity for retailers to enhance the customer relationship. During a purchase event, similar to the uncertainty about the product valuation, customers also have an uncertainty about the return process and return ease in case they need to return the product later. Customers who experience a hassle-free return and learn about the return process will not have that uncertainty and should feel less pressure about a potential product mismatch during future purchases to the extent that

their trust and loyalty are increased (Griffis et al., 2012).

There are two more potential impacts of a return event on customer repurchase behavior. First, from a service perspective, any legitimate return can be viewed as a service failure since return due to a mismatch occurs after “the service of finding the right match” fails (Mollenkopf et al., 2007a; Griffis et al., 2012). Therefore, a return experience can be viewed as a service recovery mechanism that can result in increased customer satisfaction and repurchase when managed accordingly. Second, the literature on the satisfaction-repurchase behavior link argues that ongoing customer relationships tend to be characterized by inertia that causes customers to maintain a certain level of loyalty. When it is the case, negative incidents may move the customer relationship from business as usual to a more active state (McCollough et al., 2000; Van Doorn and Verhoef, 2008). Therefore, I conjecture that a successful recovery during a negative incident such as product mismatch may lead to increased repurchase behavior. Collectively, this discussion leads to the final hypothesis:

Hypothesis 4 (H4): *Post purchase, between the two groups of customers that have the same level of satisfaction with a purchase, customers who return their purchases repurchase more than customers who do not return their purchases at all.*

2.4 Data and Definition of Variables

Diamond is a fine jewelry retail chain that sells affordable jewelry and gift items. The annual household income for its target customers is around \$50,000-\$75,000 and it has a wide product span including women’s jewelry, bridal, watches, and men’s jewelry. Diamond operates more than 1,000 stores under a primary brand name and multiple secondary brand names in the U.S. and Canada as of February 2015. The retailer also sells online. Most of the retailer’s stores are located in regional shopping centers. Diamond has a 100% money back guarantee with a no questions asked policy for items returned within 100 days after purchase.

This study requires detailed transaction level data and customer satisfaction survey data. Specific non-financial measures such as customer satisfaction constitutes only a single dimension of customer relationships. Using only this measure to predict future return or customer

repurchase behavior suffers from an omitted variable problem in an econometric sense (Nagar and Rajan, 2005). Therefore, instead of using *future return and repurchase intentions*, I use *actual return or purchase behaviors* obtained from the transaction data.

In particular, the data consists of roughly 21 million transactions and 77,000 survey responses which are not publicly available. The data from Diamond is provided under conditions of anonymity and a signed nondisclosure agreement. I spent three months at the headquarters to observe operations and understand the data. Diamond operates its stores centrally so that headquarters determine the assortment, prices, payroll, and employee training. For instance, headquarters assigns one of six assortment plans to stores depending on their sizes and the type of the mall in which they are located. As is common for most retailers, store managers have the authority to hire and terminate employees using a planned payroll budget for the year as a guideline. At Diamond, salespeople work for an hourly base salary and a percentage commission depending on their sales performance. Similarly, store managers work for a monthly base salary and get a commission on total sales. Salespeople and store managers do not receive a commission from the sales of products that are returned later. Therefore, a return reduces incentives for both store managers and salespeople. I also obtained real estate data for all stores and customer data to create some of the control variables. Table 2.1 describes dependent and independent variables used in the study. I now explain how I operationalize each variable in the model.

2.4.1 Customer Satisfaction Survey Data (CSSD)

Diamond administers pre-designed automated customer surveys online. When customers get their receipts immediately after a purchase transaction, the link to an online survey is provided at the bottom of the receipt. I obtained survey data for the 21-month period between November 2011 and July 2013. The number of surveys constitutes approximately 0.75% of all customer transactions in the same period. Of 77,465 purchases that have a corresponding survey, 12,889 result in a return, which is roughly a return rate of 16.6%.

The survey consists of 48 questions. However, I focus only on 15 key questions that are relevant to this study. The list of these questions is provided in Appendix A. All

Table 2.1: Variable construction

Variable	Type	Description	Source
<i>Dependent Variables</i>			
RETURN	Observed	An item is returned (1) or not (0)	Transaction data
REPURCHASE	Observed	Ln of \$ value of all purchases made within a year	Transaction data
<i>Independent Variables</i>			
SATISFACTION	Latent	Customer satisfaction measured using 3 questions	CSSD
PRODQUAL	Latent	Product quality measured using 3 questions	CSSD
COMPETENCE	Latent	Salesperson competence measured using 3 questions	CSSD
HELPFULNESS	Latent	Salesperson helpfulness measured using 3 questions	CSSD
ENVIRONMENT	Latent	Store environment measured using 3 questions	CSSD
<i>Control Variables</i>			
SURVEYRESPONDED	Observed	A survey was completed (1) or not (0)	Transaction data
PASTPURCHASE	Observed	Ln of \$ value of all past (1 year) purchases	Transaction data
PASTRETURN	Observed	Ln of \$ value of all past (1 year) returns	Transaction data
BASKETVALUE	Observed	Ln of \$ value of a transaction	Transaction data
BASKETSIZE	Observed	The basket size of a transaction	Transaction data
HOLIDAY	Observed	A holiday or special day purchase (1) or not (0)	Transaction data
MALLSALESQFT	Observed	Average daily revenue per square feet in the mall	Real estate data
STORESIZE	Observed	The size of a store in square feet	Real estate data
PRIMARYBRAND	Observed	A store operates under the flag brand (1) or not (0)	Real estate data
GENDER	Observed	1 for female and 0 for male	Customer data
HHINCOME	Observed	Estimated household income group for a customer	Customer data
AGE	Observed	Age of a customer	Customer data
<i>Selection Model</i>			
PASTPURCHASE, BASKETVALUE, GENDER, HHINCOME, and AGE as described above			
RESIDENCYLENGTH	Observed	A customer's length of home residency in years	Customer data
CHILD	Observed	A customer has at least one child (1) or not (0)	Customer data
<i>Notes:</i> CSSD: Customer Satisfaction Survey Data Latent variables were each measured using 5-point Likert scales. Further detail is in Appendices A and B.			

questions are rated using a 5-point Likert scale. I use three questions to measure *Product Quality* (*PRODQUAL*). As suggested in the literature (Dabholkar et al., 1996), product quality items include both direct quality questions and a product availability question since Diamond stores operate under different assortment plans. Moreover, limited product selection may increase the likelihood of a mismatch between product quality and customers' quality expectations (Finn and Kayande, 2004). I measure *Salesperson Competence* (*COMPETENCE*) using three questions, *Salesperson Helpfulness* (*HELPFULNESS*) using three questions, and *Store Environment* (*ENVIRONMENT*) using three questions.

I also note that I measure each quality dimension from a customer's perspective. Therefore, any quality dimension I discuss hereafter should be considered as the customer's per-

ceived quality, not actual objective quality. Perceived quality is a global assessment and a higher-level abstraction rather than a specific attribute of a product. Zeithaml (1988) explains the difference between perceived quality and actual quality.

Similar to literature that uses both satisfaction and loyalty intentions to measure the overall satisfaction (McKinney et al., 2002), I use three questions to measure *Customer Satisfaction (SATISFACTION)*: satisfaction, repurchase intention, and recommendation (word-of-mouth) intention. The rationale for this measurement is that these three questions can be leading indicators of future business performance (Morgan and Rego, 2006). Therefore, they can be used together to measure overall satisfaction so long as repurchase and recommendation intentions are not correlated with actual behaviors. The low correlation (i.e. 0.02) between the actual repurchase behavior and repurchase intention in the data provides support to use the three questions to measure the overall satisfaction.

2.4.2 Transaction Data

Transaction data are available for the 4.5 year period between August 2009 and December 2013. The wide time range allows to observe the actual past and future purchase and return behavior of customers who participated in the survey. Diamond has a 100-day return policy. Since the transaction data covers an additional 1.5 years after the last customer satisfaction survey data were collected, I do not have a censoring problem. I am able to tie each survey to its corresponding purchase transaction.

I generate the binary variable RETURN for each transaction to indicate whether a purchase resulted in a return ($\text{RETURN} = 1$) or not ($\text{RETURN} = 0$). In line with the literature (Seiders et al., 2005; Voss et al., 2010; Griffis et al., 2012), I operationalize *Customer Repurchase Behavior (REPURCHASE)* as the \$ value of all purchases made within one year of a purchase transaction. I take the natural log of REPURCHASE to improve distribution normality. Later in the robustness test, I also define REPURCHASE as the number of items purchased and the number of purchase visits (i.e. transactions) made within one year of the purchase event. Moreover, the transaction data allow to identify each customer's past purchase and return behaviors as control variables. I explain how I operationalize past purchase

and return behaviors in the next section.

2.4.3 Control Variables

I include a set of control variables to address sample selection, and to capture customer past purchase and return behavior, customer demographics, store characteristics, and transaction characteristics that may potentially influence return and repurchase behaviors. Survey response (SURVEYRESPONDED) is a binary variable and is denoted as “1” if a customer responds to the survey and “0” otherwise. As with REPURCHASE, I measure historical purchase and return behavior of each customer (PASTPURCHASE and PASTRETURN) as the \$ value for all purchases and returns made up to one year prior to the purchase event. Mall sales square feet (MALLSALESQFT) indicates the average daily revenue per square feet that a small-sized store (such as jewelry stores) makes in a mall. I use this variable to control for the quality and the competitive environment of the mall in which a store is located. Store size (STORESIZE) denotes the total square feet of a store. Primary brand name (PRIMARYBRAND) indicates whether a store operates under the primary brand name or not.

I also control for demographics such as household income (HHINCOME), age (AGE), gender (GENDER), children (CHILD), and approximate length of residency in years (RESIDENCYLENGTH) for customers at their current home address. HHINCOME is an ordinal variable that ranges between 1 (for household income less than \$15,000) and 9 (for household income greater than \$125,000). Finally, I control for transaction characteristics including the total amount of the transaction (BASKETVALUE) since more expensive products are more likely to be returned (Anderson et al., 2006; Hess and Mayhew, 1997), the basket size of a transaction (BASKETSIZE), and whether the transaction is completed within 10 days before a holiday or special day (e.g. Christmas, Mother’s Day) period or not (HOLIDAY).

I provide descriptive statistics and a correlation matrix of all variables in Table 2.2. I also examined the variance inflation factor (VIF) to check for multicollinearity. With the VIF score mean 1.49 and range between 1.02 and 3.52, well below the rule-of-thumb cut-off of 10 (Neter et al., 1990), there is no evidence of multicollinearity in this data set.

Table 2.2: Descriptive statistics and correlation matrix

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. RETURN	0.14	0.35	0	1	1.00										
2. REPURCHASE	2.34	3.08	0	12.5	0.25	1.00									
3. SATISFACTION	4.66	0.56	1	5	-0.04	0.06	1.00								
4. PRODQUAL	4.58	0.52	1	5	-0.07	0.03	0.66	1.00							
5. COMPETENCE	4.39	0.65	1	5	-0.00	0.07	0.64	0.65	1.00						
6. HELPFULNESS	4.74	0.43	1	5	-0.03	0.02	0.66	0.66	0.66	1.00					
7. ENVIRONMENT	4.59	0.53	1	5	-0.03	0.04	0.72	0.72	0.73	0.78	1.00				
8. SURVEYRESP	0.44	0.50	0	1	0.06	0.25	-	-	-	-	-	1.00			
9. PASTPURCHASE	1.91	2.98	0	12.6	0.06	0.30	0.05	0.03	0.06	0.02	0.04	0.03	1.00		
10. PASTRETURN	0.47	1.69	0	12.2	0.09	0.22	0.02	0.00	0.03	0.00	0.01	0.02	0.51	1.00	
11. BASKETVALUE	5.49	1.24	0.17	11.5	0.13	0.14	0.02	0.03	0.08	0.01	0.01	0.10	0.02	0.03	1.00
12. BASKETSIZE	1.39	1.14	1	41	0.07	0.10	0.01	0.00	0.02	0.01	-0.00	0.04	0.06	0.03	0.08
13. HOLIDAY	0.37	0.48	0	1	-0.02	-0.04	-0.02	-0.02	-0.04	-0.02	-0.03	-0.05	-0.05	-0.04	-0.06
14. MALLSALESQFT	430.28	168.03	120	1514	0.01	-0.03	-0.05	-0.06	-0.05	-0.06	-0.07	-0.02	-0.03	0.00	0.05
15. STORESIZE	1765.03	503.68	948	6315	0.01	0.02	0.01	0.02	0.02	0.00	0.02	0.01	0.02	0.02	0.03
16. PRIMARYBRAND	0.53	0.50	0	1	0.02	0.01	0.04	0.07	0.07	0.05	0.06	-0.03	0.02	0.01	0.07
17. GENDER	0.44	0.50	0	1	0.02	0.03	0.00	0.01	-0.02	0.00	0.00	0.07	0.01	0.06	-0.12
18. HHINCOME	5.23	2.24	1	9	0.00	0.01	-0.02	-0.03	-0.02	-0.00	-0.01	0.03	0.01	0.00	0.02
19. AGE	43.95	14.00	13	109	-0.02	-0.00	0.01	-0.01	-0.02	0.03	0.02	0.02	0.01	-0.00	-0.07
20. RESLENGTH	7.33	5.41	0	15	-0.02	0.00	0.01	0.01	0.00	0.02	0.02	-0.01	0.01	-0.00	-0.03
21. CHILD	0.40	0.49	0	1	0.01	-0.01	0.00	-0.00	-0.00	-0.00	-0.00	-0.01	-0.02	-0.01	-0.02
Variable					12	13	14	15	16	17	18	19	20	21	
12. BASKETSIZE					1.00										
13. HOLIDAY					0.02	1.00									
14. MALLSALESQFT					-0.00	-0.03	1.00								
15. STORESIZE					0.01	-0.02	0.12	1.00							
16. PRIMARYBRAND					-0.01	0.03	-0.13	-0.08	1.00						
17. GENDER					0.04	-0.07	0.01	0.03	-0.03	1.00					
18. HHINCOME					0.01	0.02	0.07	0.06	-0.03	-0.03	1.00				
19. AGE					0.06	0.04	-0.05	0.02	-0.04	0.07	0.18	1.00			
20. RESLENGTH					0.02	0.03	-0.02	-0.00	0.01	0.04	0.15	0.22	1.00		
21. CHILD					0.00	0.01	-0.00	-0.00	-0.00	0.02	0.12	-0.07	-0.03	1.00	

Except for cells in bold-italic, all coefficients are significant at $p < 0.05$ level.

2.5 Research Methodology

I conduct a confirmatory factor analysis (CFA) for latent variables. The results are displayed in Appendix B. The CFA indicates that (1) the theoretical model fits the data and (2) the scales are valid and reliable. Therefore, following Nagar and Rajan (2005) and Siemsen et al. (2009), I use scale averages as latent variable scores in estimating the models.

I next develop the econometric specifications for testing the hypotheses. I first focus on the binary regression model (1) to identify the key drivers of returns and (2) to test hypotheses H1-H3. Then, I introduce an OLS model for hypothesis H4 to assess the moderation role of returns upon repurchase behavior. Next, I discuss the treatment effect model to address the potential sample selection in all models.

2.5.1 Binary Regression Model for Returns

The binary nature of the observed outcome variable for returns (RETURN) necessitates the use of a binary choice model such as the logit or probit models (Greene, 2012). These models are a good fit for the utility-choice framework since they model the difference in utility between two possible actions (return or keep the product) as a linear combination of observed variables ($\mathbf{X}\beta$) plus a random variable (ϵ). Therefore, any estimated coefficient in these models is interpreted as the impact of a covariate on the utility from returning a product. Since ϵ is stochastic, these models can only predict the probability of returning a product over keeping it. I define the model as:

$$\begin{aligned}
 Prob(RETURN_i = 1|x) &= \Phi(\beta_0 + \beta_1 SATISFACTION_i + \beta_2 PRODQUAL_i + \beta_3 COMPETENCE_i \quad (2.1) \\
 &\quad + \beta_4 COMPETENCE_i^2 + \beta_5 HELPFULNESS_i + \beta_6 ENVIRONMENT_i \\
 &\quad + \beta_7 SURVEYRESPONDED_i + \mathbf{T}_i\beta_c + \mathbf{W}_i\beta_t + \mathbf{Z}_i\beta_s) \\
 SATISFACTION_i &= \theta_0 + \theta_1 PRODQUAL_i + \theta_2 COMPETENCE_i + \theta_3 HELPFULNESS_i \\
 &\quad + \theta_4 ENVIRONMENT_i + e_i
 \end{aligned}$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution function; \mathbf{T}_i is a vector of customer-specific control variables including PASTPURCHASE, PASTRETURN, GEN-

DER, HHINCOME, and AGE; \mathbf{W}_i is a vector of transaction-specific control variables including BASKETVALUE, BASKETSIZE, and HOLIDAY; and \mathbf{Z}_i is a vector of store-specific control variables including MALLSALESQFT, STORESIZE, and PRIMARYBRAND. The subscripts c , t , and s on the three beta vectors indicate that β_c is a vector of coefficients related to customer specific control variables, β_t , is a vector of coefficients related to transaction specific control variables, and β_s is a vector of coefficients related to store specific control variables. SURVEYRESPONDED is a binary variable for the sample selection model that I discuss in section 2.5.3.

Note that the latent variable SATISFACTION is a mediator between PRODQUAL, COMPETENCE, HELPFULNESS, ENVIRONMENT, and RETURN. Therefore, I also specify the regression equation for SATISFACTION. The key variables to assess H1-H3 are SATISFACTION, PRODQUAL, COMPETENCE, COMPETENCE², HELPFULNESS, and ENVIRONMENT in the probit model, respectively.

2.5.2 OLS Model for Repurchase Behavior

Recall that REPURCHASE is a continuous variable. Therefore, I specify the model as an OLS regression:

$$\begin{aligned} \text{REPURCHASE}_i &= \alpha_0 + \alpha_1 \text{SATISFACTION}_i + \alpha_2 \text{RETURN}_i + \alpha_3 \text{SATISFACTION}_i \times \text{RETURN}_i & (2.2) \\ &+ \alpha_4 \text{SURVEYRESPONDED}_i + \mathbf{T}_i \alpha_c + \mathbf{W}_i \alpha_t + \mathbf{Z}_i \alpha_s + \xi_i \\ \text{SATISFACTION}_i &= \theta_0 + \theta_1 \text{PRODQUAL}_i + \theta_2 \text{COMPETENCE}_i + \theta_3 \text{HELPFULNESS}_i \\ &+ \theta_4 \text{ENVIRONMENT}_i + e_i \end{aligned}$$

where the interaction term $\text{SATISFACTION}_i \times \text{RETURN}_i$ represents the marginal effect of RETURN to vary with SATISFACTION. As in the binary regression model, I specify the regression equation for the mediator variable SATISFACTION. The key variable to assess H4 is the interaction term $\text{SATISFACTION}_i \times \text{RETURN}_i$ in Equation 2.2.

2.5.3 Selection Model

One can argue that customers complete surveys only if they are extremely happy or extremely angry with the service they get at the point of purchase. Moreover, responding to a survey is not randomized since customers themselves decide whether or not to complete the survey. Therefore, customer satisfaction surveys inherently embody self-selection.

Survey-based studies often use early vs. late response comparisons to show that selection bias is not a concern (Armstrong and Overton, 1977). This approach is based on the assumption that individuals who respond later can be used as a proxy to non-respondents. Using transaction data and customer data, I am able to directly compare respondents to non-respondents as well as early respondents to late respondents. I find that even though in some cases early respondents and late respondents are not statistically different, customers who completed the survey have statistically different return and repurchase behaviors from those who did not complete the survey. Therefore, assuming late respondents represent behaviors of non-respondents and such behaviors are identical to early respondents is difficult to substantiate for this study. When this assumption does not hold, a selection problem exists. In that case, an empirical model that does not account for sample selection can generate misleading estimates and conclusions (Heckman, 1979; Maddala, 1983; Ghosh and John, 2009).

Extant literature has identified multiple methods to address self-selection. The two most common methods heavily used in the literature are Heckman models (Heckman, 1979) and the treatment effect model (Greene, 2012). Heckman models are used when (1) the dependent variable is observed only if selection occurs and (2) the dummy variable that indicates the selection condition does not appear in the regression equation. The treatment effect model differs from Heckman models in two aspects. First, the dependent variable is observed regardless of the selection. Second, the dummy variable indicating the selection condition is directly entered into the regression equation.

Diamond offers its customers a \$100 discount on their next purchases of \$300 or more if they complete the online survey. Therefore, it is reasonable to assume that any customer

who completes the survey is very likely to purchase more items in the future to benefit from the discount offer. Moreover, the \$100 discount may incentivize some customers to exchange the item they purchase with a more expensive item. As a result, I can expect that completing the survey might increase both returns and repurchase behavior. Moreover, using transaction data, I am able to observe SATISFACTION and REPURCHASE variables for all customers regardless of whether or not they complete the survey. For these reasons, I use the treatment effect model in this analysis.

Customers have the choice of whether or not to respond to the survey. Customers will respond if they believe the net utility from responding is nonnegative given their idiosyncratic characteristics. In evaluating the effect of completing the survey on return and repurchase behavior, it is important to account for truncation in both dependent variables owing to the self-selection by customers in their survey response choice. The endogenous switching regression model addresses this concern. Specifically, this model is expressed in two equations:

$$y_i = \mathbf{X}_i\beta + \delta\text{SURVEYRESPONDED}_i + u_i \quad (2.3)$$

$$\text{SURVEYRESPONDED}_i^* = \mathbf{R}_i\gamma + v_i \quad (2.4)$$

$$\text{SURVEYRESPONDED}_i = \begin{cases} 1 & \text{if } \text{SURVEYRESPONDED}_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

where y_i (δ) in Equation 2.3 corresponds to $\text{Prob}(\text{RETURN}_i = 1|x)$ (β_7) and REPURCHASE_i (α_4) in Equations 2.1 and 2.2, respectively; $\text{SURVEYRESPONDED}_i^*$ represents the unobserved benefit from completing the survey; \mathbf{R}_i is a vector of independent variables representing a customer's idiosyncratic characteristics including PASTPURCHASE, BASKET-VALUE, GENDER, HHINCOME, AGE, RESIDENCYLENGTH, and CHILD; and v_i is the error term. Although $\text{SURVEYRESPONDED}_i^*$ is not observed, I can observe the actual decision SURVEYRESPONDED_i of each customer. Assuming v_i to be normally distributed, $v_i \sim N(0, \sigma^2)$, the selection model becomes a probit model. To complete the model speci-

fication, I assume that the error term pair (u_i, v_i) has a bivariate normal distribution with mean 0 and covariance matrix $\begin{bmatrix} \sigma & \rho \\ \rho & 1 \end{bmatrix}$, where ρ is the correlation between u and v .

Multiple studies in the literature estimate the treatment effect model for different contexts when Equation 2.3 is a single regression equation. However, in my case, Equation 2.3 is a set of equations consisting recursive simultaneous equations that include a mediator variable in all models. I am not aware of any study in the Marketing and Operations Management literature that applies the treatment effect model to recursive simultaneous equation models. I adapt methodology from econometrics literature (Skron dal and Rabe-Hesketh, 2004) that uses the full information maximum likelihood (FIML) approach to estimate the treatment effect model with recursive models. The FIML approach assumes that missing data to be at least missing at random (MAR) and estimates a likelihood function for each transaction based on the variables that are present so that all available data are used. I operationalize this approach by:

- including a dummy latent variable L with two indicators: y_i and SURVEYRESPONDED $_i$,
- constraining the coefficient of the path from L to SURVEYRESPONDED $_i$ to be 1 and,
- constraining the variance of L to be 1.

Let β^* , γ^* , and σ^{2*} be the estimated parameters in the model. Now, let κ denote the coefficient of L in Equation 2.3. Note that due to the increased residual variance in the selection model, the coefficients in the selection model are expected to increase by a factor of $\sqrt{1 + \sigma^{2*}}$. Therefore, I need to apply the following transformation to obtain the parameters in the standard probit model:

$$\beta = \beta^*; \gamma = \gamma^* / \sqrt{1 + \sigma^{2*}}; \sigma = \sigma^{2*} + \kappa^2; \text{ and } \rho = \kappa / \sqrt{(\kappa^2 + \sigma^{2*})(1 + \sigma^{2*})} \quad (2.5)$$

Note that this approach is not restricted to only recursive simultaneous equation models. The approach can also be applied to other models with observed variables within a single

regression equation and structural equation models with latent variables. I estimate all parameters using Stata13 (Stata-Corp., 2014). In all regressions, I use robust standard errors clustered at the store level to account for nonindependence of observations from the same store. I next present the findings.

2.6 Results

2.6.1 *The Return Model*

Recall that the survey data are available for the time period between November 2011 and July 2013. For the same time period, there are 9,248,600 item-level transactions in the transaction data. I use the rest of the transaction data to create PASTPURCHASE, PASTRETURN, and REPURCHASE variables for every customer. Since the survey data relate to the transaction level, I also aggregate the item-level transactions into the transaction-level. Doing so gives 6,086,273 transactions for the survey time period, of which 73,598 transactions have a corresponding survey. Overall, I identify 6,012,675 non-respondents. For this analysis, I randomly sample 100,000 non-respondents and merge the corresponding data with the 73,598 respondents. This process generates a sample size of 173,598 for the analysis. I use this data to test H1-H3 on the first (the Probit) model. Later in the robustness check, I show that different samples and sample sizes do not change the results.

Table 2.3 provides results for the RETURN model. Model-1 is the baseline model that incorporates only the control variables and the sample selection model. To analyze the mediating effect of SATISFACTION, I use the causal steps procedure introduced by Baron and Kenny (1986). This approach involves the comparison of three models: One model in which the dependent variable is regressed on the independent variables to show direct effect (Model-2); a second model in which the mediated variable is regressed on the independent variables (Model-3); and a third model in which the dependent variable is regressed on both the independent variables and the mediator (Model-4). I test H1-H3 based on the estimated results on Model-4. Model fit statistics (Wald χ^2 and R^2) indicate a good fit in all models. Moving from Model-1 to Model-4 increases model fit significantly ($\Delta\chi^2(df) = 298(6)$, $p <$

0.001).

Table 2.3: Estimation results for the return model

Model	Variables	Model-1	Model-2	Model-3	Model-4
\mathbb{Z} EDIATION	Intercept			0.80*** (0.016)	0.80*** (0.028)
	PRODQUAL			0.23*** (0.004)	0.23*** (0.007)
	COMPETENCE			0.10*** (0.003)	0.10*** (0.005)
	HELPFULNESS			0.28*** (0.005)	0.28*** (0.009)
	ENVIRONMENT			0.23*** (0.005)	0.23*** (0.009)
\mathbb{R} ETURN	Intercept	-0.14*** (0.011)	1.42*** (0.351)		-1.08* (0.466)
	SATISFACTION				-0.09* (0.036)
	PRODQUAL		-0.25*** (0.065)		-0.46*** (0.038)
	COMPETENCE		-0.32* (0.139)		-0.50* (0.228)
	COMPETENCE ²		0.05** (0.018)		0.07** (0.027)
	HELPFULNESS		-0.01 (0.025)		0.01 (0.049)
	ENVIRONMENT		0.08** (0.033)		0.19*** (0.046)
\mathbb{C} ONTROLS	PASTPURCHASE	-0.00 (0.001)	0.01** (0.003)		0.00 (0.005)
	PASTRETURN	0.02*** (0.001)	0.04*** (0.011)		0.07*** (0.008)
	GENDER	-0.02*** (0.003)	-0.02 (0.042)		0.02 (0.025)
	HHINCOME	-0.00* (0.001)	-0.00 (0.004)		-0.01 (0.006)
	AGE	-0.00*** (0.000)	-0.00*** (0.000)		-0.00*** (0.001)
	BASKETVALUE	0.02*** (0.001)	0.01 (0.038)		0.11*** (0.011)
	BASKETSIZE	0.02*** (0.001)	0.05*** (0.010)		0.08*** (0.000)
	HOLIDAY	0.01* (0.003)	0.03† (0.015)		0.02 (0.024)
	MALLSALESQFT	0.03*** (0.008)	0.06 (0.047)		0.00 (0.000)
	STORESIZE	0.00 (0.003)	0.01 (0.017)		0.00 (0.000)
	PRIMARYBRAND	0.01* (0.003)	0.03 (0.018)		0.05 (0.031)
	SURVEYRESPONDED	0.49*** (0.007)	0.45*** (0.008)		0.25*** (0.008)
\mathbb{O} ELECTION	Intercept	-0.93*** (0.028)	-1.26*** (0.038)		-1.22*** (0.051)
	PASTPURCHASE (\$)	0.00 (0.002)	-0.01*** (0.002)		0.00 (0.002)
	BASKETVALUE	0.08*** (0.004)	0.11*** (0.005)		0.13*** (0.007)
	GENDER	0.19*** (0.009)	0.14*** (0.011)		0.31*** (0.014)
	HHINCOME	0.01*** (0.002)	0.01** (0.003)		0.02*** (0.004)
	AGE	0.01*** (0.000)	0.00*** (0.000)		0.08*** (0.001)
	RESIDENCYLENGTH	-0.01*** (0.001)	-0.01*** (0.001)		-0.01*** (0.001)
	CHILD	-0.01 (0.008)	-0.01 (0.009)		-0.02 (0.019)
χ^2 (df)		455(12)	748(17)	-	753(18)
ρ		-0.69***	-0.81**	-	-0.82**
R^2		-	-	0.58	-

Notes: † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Clustered robust standard errors are presented in parentheses.

As seen in Model-4, SATISFACTION ($\beta = -0.09$, $p < 0.05$) is negatively associated with returns, providing support for H1. This finding suggests that managers may prevent returns by monitoring and influencing customer satisfaction at the point of purchase. I also find that PRODQUAL ($\beta = -0.46$, $p < 0.001$) is negatively associated with returns, providing

support for H2. As I expect, a product with high quality perceived by a customer is less likely to be returned.

I note that both linear and quadratic terms for COMPETENCE are significant, but the coefficient is positive for the linear term ($\beta = -0.50, p < 0.05$) and negative for the quadratic term ($\beta = 0.07, p < 0.01$). Although this is necessary to claim a U-shaped relationship between COMPETENCE and RETURN, it is not sufficient. To support this relationship, I perform further analysis using the Box-Whisker plot of the data (Gokpinar et al., 2010) and the marginal effect of COMPETENCE (Siemsen et al., 2009). Note that Probit coefficients represent a change in the linear z-score predictor as a result of a change in an independent variable. Different coefficient signs of linear and quadratic terms of COMPETENCE make it difficult to draw a conclusion about the overall effect of COMPETENCE on returns. Therefore, I estimate predicted values for return probability and mean marginal effects to understand the overall effect of COMPETENCE.

Figure 2.4(a) shows the predicted return probabilities at various salesperson competence levels. The figure demonstrates that on average, an increase from 1 to 2 (2 to 3) in COMPETENCE reduces the probability of a return by 15% (8%). The decrease in the probability of return due to an increase in COMPETENCE diminishes at the COMPETENCE threshold value of 3.75. After the threshold, an increase from 4 to 5 in COMPETENCE *increases* the probability of a return by 6%. This supports the U-shaped relationship. The Box-Whisker plots in Figure 2.4(b) provides a simple visualization of the predicted return probabilities at different levels of COMPETENCE, also supporting the U-shaped relationship. Finally, as seen in Figure 2.4(c), the marginal effect of COMPETENCE on predicted return probabilities remains negative up to the COMPETENCE threshold value of 4 and becomes positive after the threshold, indicating a U-relationship. Hence, I conclude that the model supports the U-shaped relationship between COMPETENCE and RETURN (H3a).

For salesperson helpfulness and store environment, I observe some interesting and counterintuitive results. I find that HELPFULNESS is not significant. I also observe that, even though significant, the coefficient of ENVIRONMENT ($\beta = 0.19, p < 0.001$) is positive. In

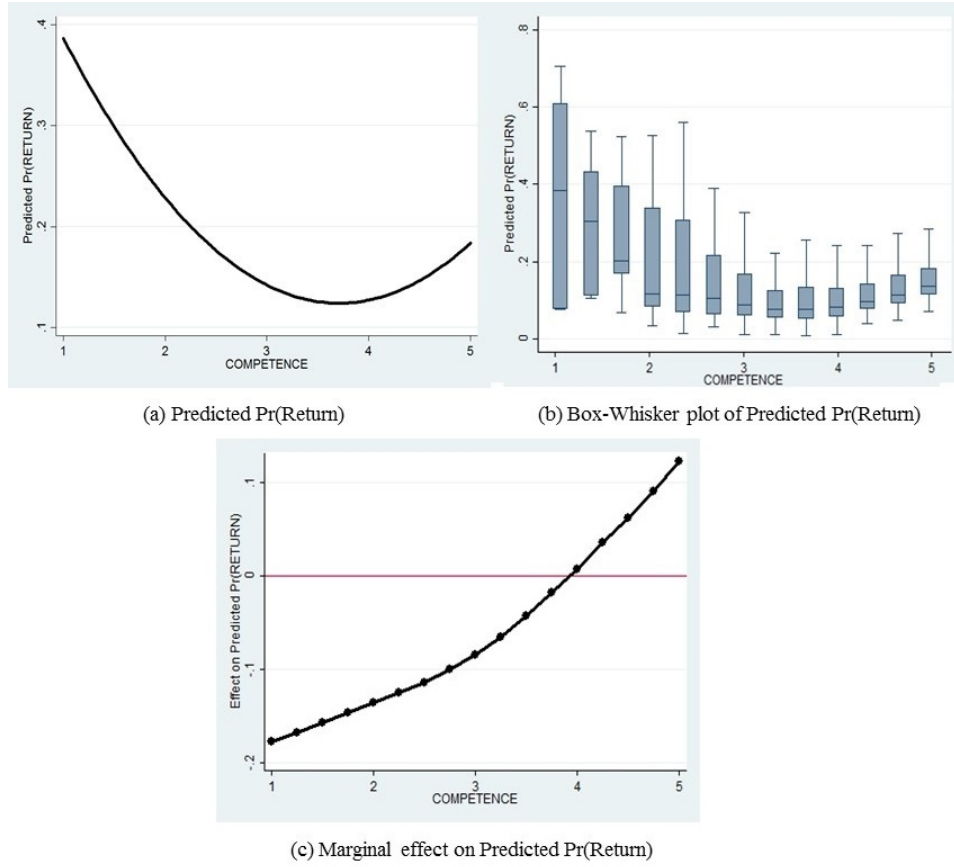


Figure 2.4: Analysis of U-shaped relationship between COMPETENCE and RETURN

contrast to the hypothesis, I see that pleasant store environments appear to *increase* returns. Therefore, H3b is not supported.

In the theoretical model, I implicitly hypothesize that SATISFACTION partially mediates the effects of product quality and service quality elements on RETURN. To establish this hypothesis, the direct effects of product quality and service quality elements (1) on RETURN (Model-2) should be significant; (2) on SATISFACTION (Model-3) should be significant; and (3) on RETURN when controlling for SATISFACTION (Model-4) should be significant. Overall, Models 2 to 4 demonstrate that SATISFACTION partially mediates the effect of PRODQUAL, COMPETENCE, and ENVIRONMENT.

Among the key controls, I find that PASTRETURN, BASKETVALUE, and BASKET-

SIZE are positively associated with returns, indicating customers who historically return more, who purchase more expensive items, and who purchase higher quantities return more. I also find that sample selection is significant ($\rho = -0.82, p < 0.01$) in the data and customers who complete the survey are more likely to return.

2.6.2 The Repurchase Model

To test H4 on the second model (Equation 2.2), I create a different dataset. Note that I operationalize the REPURCHASE variable based on each customer's future purchases made within a year of the original transaction time. Also note that the transaction data are available up to December 31, 2013, implying that any survey completed between January 2013 and July 2013 does not have a complete one year of associated transaction records to generate the REPURCHASE variable. Therefore, to avoid censoring problems, I eliminate all observations with a transaction date between January 2013 and July 2013 in the sample dataset that I use for the first model. Doing so gives a second dataset with a sample size of 120,312 to estimate the REPURCHASE model.

Table 2.4 provides results for the REPURCHASE model. Model-5 is the baseline model that incorporates only the control variables and selection model. Similar to what I do in the RETURN model, I estimate three models to analyze the mediation effect. Model-6 shows the direct effects of independent variables on REPURCHASE. Model-7 is a simple OLS regression for the mediating variable SATISFACTION. Model-8 is the theoretical model that I use to assess H4. Model-9 is the full model with all direct effects and the mediating variable. Note that I include RETURN and SATISFACTIONxRETURN variables in Model-8 to test the moderating effect of RETURN. Model fit statistics (Wald χ^2 and R^2) indicate a good fit in all models. Moving from Model-5 to Model-8 increases model fit significantly ($\Delta\chi^2(df) = 1,532(3), p < 0.001$).

Model-8 shows that the main effects SATISFACTION ($\beta = 0.42, p < 0.001$) and RETURN ($\beta = 3.59, p < 0.001$) are significant. Yet, in contrast to the hypothesis, while significant, the interaction term SATISFACTIONxRETURN ($\beta = -0.40, p < 0.001$) is negatively associated with returns. Therefore, H4 is not supported. To better understand the

Table 2.4: Estimation results for the repurchase model

Variables	Model-5	Model-6	Model-7	Model-8	Model-9
Intercept			0.76*** (0.020)	0.76*** (0.035)	0.76*** (0.035)
PRODQUAL			0.23*** (0.005)	0.23*** (0.009)	0.23*** (0.009)
COMPETENCE			0.10*** (0.004)	0.10*** (0.006)	0.10*** (0.006)
HELPFULNESS			0.28*** (0.006)	0.28*** (0.011)	0.28*** (0.011)
ENVIRONMENT			0.23*** (0.006)	0.23*** (0.011)	0.23*** (0.011)
Intercept	3.39*** (0.295)	3.22*** (0.437)		1.26** (0.406)	1.79*** (0.447)
SATISFACTION				0.42*** (0.055)	0.49*** (0.074)
RETURN				3.59*** (0.525)	3.52*** (0.529)
SATISxRET				-0.40*** (0.111)	-0.39*** (0.111)
PRODQUAL		-0.13† (0.077)			-0.07 (0.077)
COMPETENCE		0.24*** (0.061)			0.16** (0.060)
HELPFULNESS		-0.14 (0.097)			-0.22* (0.097)
ENVIRONMENT		0.13* (0.037)			-0.04 (0.096)
PASTPURCHASE	0.24*** (0.008)	0.25*** (0.009)		0.24*** (0.009)	0.24*** (0.009)
PASTRETURN	0.11*** (0.014)	0.09*** (0.016)		0.06*** (0.016)	0.06*** (0.016)
GENDER	-0.17*** (0.050)	-0.19*** (0.055)		-0.28*** (0.054)	-0.28*** (0.054)
HHINCOME	-0.02** (0.011)	-0.03** (0.012)		-0.03** (0.012)	-0.03** (0.012)
AGE	-0.01*** (0.002)	-0.01** (0.002)		-0.01** (0.002)	-0.01** (0.002)
BASKETVALUE	0.23*** (0.021)	0.23*** (0.023)		0.20*** (0.022)	0.20*** (0.022)
BASKETSIZE	0.13*** (0.015)	0.13*** (0.018)		0.10*** (0.016)	0.10*** (0.016)
HOLIDAY	-0.13** (0.044)	-0.17*** (0.049)		-0.17*** (0.048)	-0.17*** (0.048)
MALLSALESQFT	-0.12 (0.167)	-0.15 (0.168)		-0.17 (0.000)	-0.17 (0.000)
STORESIZE	0.00 (0.052)	0.02 (0.056)		0.00 (0.000)	0.00 (0.000)
PRIMARYBRAND	0.06 (0.053)	0.11† (0.059)		0.11† (0.058)	0.10† (0.057)
SURVEYRESPONDED	0.75*** (0.017)	0.79*** (0.019)		0.83*** (0.021)	0.82*** (0.020)
Intercept	-1.12*** (0.040)	-1.23*** (0.041)		-0.51*** (0.028)	-0.51*** (0.028)
PASTPURCHASE (\$)	0.00 (0.002)	-0.01*** (0.002)		0.00** (0.001)	0.00** (0.001)
BASKETVALUE	0.11*** (0.005)	0.11*** (0.005)		0.05*** (0.003)	0.05*** (0.003)
GENDER	0.20*** (0.012)	0.15*** (0.013)		0.11*** (0.007)	0.11*** (0.007)
HHINCOME	0.01** (0.003)	0.01*** (0.004)		0.01*** (0.002)	0.01*** (0.002)
AGE	0.01*** (0.000)	0.00† (0.000)		0.00*** (0.000)	0.00*** (0.000)
RESIDENCYLENGTH	-0.00*** (0.001)	-0.01*** (0.001)		-0.00*** (0.001)	-0.00*** (0.001)
CHILD	-0.00 (0.011)	-0.00 (0.012)		-0.00 (0.006)	-0.00 (0.006)
χ^2 (df)	1,384(12)	1,598(16)		2,916(15)	2,925(19)
ρ	-0.42***	-0.42***		-0.20***	-0.21***
R^2			0.54		

Notes: † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Clustered robust standard errors are presented in parentheses.

interaction effect of RETURN on the satisfaction-repurchase behavior link, I provide a corresponding conditional effect plot (Aiken et al., 1991) in Figure 2.5. The figure demonstrates the predicted natural log-transformed REPURCHASE for returners and non-returners with respect to SATISFACTION. The shaded area around each line indicates the 95% confidence interval. I find that, when all other variables are held fixed at their means, on average, a return event results in a \$171 increase in customer repurchase behavior. Even though the

figure implies that the increase in repurchase behavior due to a return event is higher for dissatisfied customers than for satisfied customers, one should be cautious with the interpretation. When I transform the numbers into \$ values, I see that on average, a return event increases a dissatisfied (SATISFACTION= 1) customer's repurchase behavior from \$6 to \$154. For a satisfied customer (SATISFACTION= 5), a return event increases repurchase behavior from \$31 to \$208, implying that the revenue increase due to a return event is higher for satisfied customers than for dissatisfied customers.

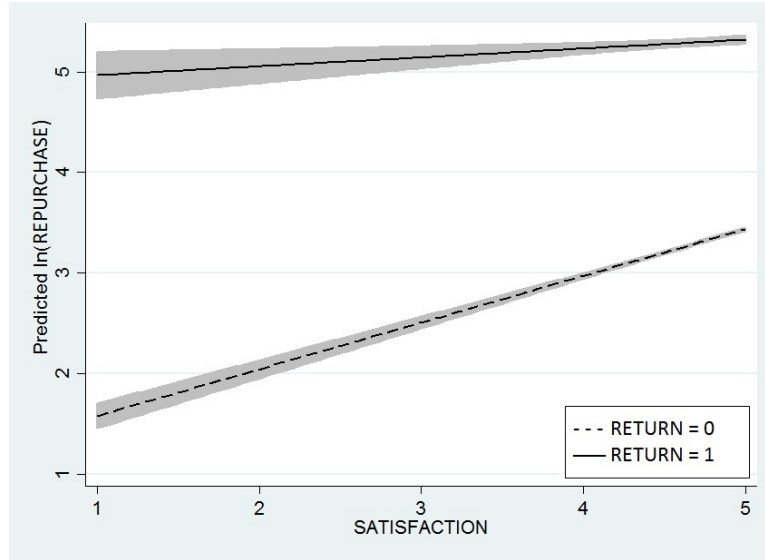


Figure 2.5: The effect of return on customer repurchase behavior

To test the mediation effect, I follow the same procedure as in the RETURN model. When I consider models 6, 7, and 9 collectively, I find that SATISFACTION completely mediates the effect of PRODQUAL and ENVIRONMENT on REPURCHASE and partially mediates the effect of COMPETENCE on REPURCHASE. For the key control variables, I observe that customers who historically buy and return more (PASTPURCHASE, PASTRETURN), purchase more expensive items (BASKETVALUE), and purchase high quantities (BASKETSIZE), purchase more in the future. I also find that sample selection is significant

($\rho = -0.21$, $p < 0.001$) in the data and customers who complete the survey purchases more in the future than those who do not complete the survey. This, of course, is not surprising given that survey respondents are offered a discount coupon on future purchases.

2.6.3 Post Hoc Analysis

I conduct the analysis on return and repurchase behaviors to this point without consideration of the time elapsed between an initial purchase and a subsequent return event. Recall that Diamond has a 100-day return policy. The average time to return (TTR) a product in the data is three weeks. While there are numerous customers who return the product on the day they purchase, it is also possible to see a return three months after the original purchase. The varying TTRs may arise simply due to the fact that customers have different shopping and return behaviors. Therefore, I conduct a post hoc analysis to assess how return and repurchase behaviors change for returns that occur at different times.

2.6.3.1 The Return Behavior for Different TTRs

I divide returns in the sample into five groups: returns that occur (1) on the day of purchase (0-day), (2) between day 1 and day 6, (3) between day 7 and day 15, (4) between day 16 and day 45, and (5) after 45 days. Each group constitutes approximately 20% of all returns.

Table 2.5: Estimation results for the return model for different TTR groups

TTR		Key Independent Variables									
		SATISFACTION		PRODQUAL		COMPETENCE		COMPETENCE ²		HELPFULNESS	
0	0-day	-0.09	(0.076)	0.10	(0.109)	-0.39	(0.366)	0.07†	(0.044)	0.05	(0.117)
1	1-6 days	-0.14*	(0.058)	-0.53***	(0.060)	-0.44†	(0.295)	0.07†	(0.041)	-0.03	(0.077)
2	7-15 days	-0.11*	(0.049)	-0.46***	(0.060)	-0.52*	(0.297)	0.07†	(0.040)	0.07	(0.080)
3	16-45 days	-0.01	(0.056)	-0.40***	(0.058)	0.03	(0.364)	-0.00	(0.044)	-0.08	(0.073)
4	>45 days	-0.03	(0.067)	-0.33***	(0.066)	-0.74*	(0.314)	0.10*	(0.047)	0.06	(0.085)
ENVIRONMENT											
0	0-day	-0.31**	(0.105)								
1	1-6 days	0.27***	(0.081)								
2	7-15 days	0.21**	(0.075)								
3	16-45 days	0.24***	(0.072)								
4	>45 days	0.10	(0.082)								

I next estimate the RETURN model (Equation 2.1) with TTR grouping. I present the findings for the key independent variables in Table 2.5. I observe that except for the store environment, customer purchase experience is not significant to explain return behaviors of customers who return product on the day of original purchase. In contrast to the findings from the entire dataset, store environment is negatively associated with 0-day returns. The main findings from the RETURN model are consistent with the findings for customers who return their purchases between the first two weeks (TTR=1 and 2). I observe that for TTR=3 (TTR=4), only PRODQUAL and ENVIRONMENT (COMPETENCE) are significant, indicating that satisfaction with a purchase experience does not influence late return behaviors.

2.6.3.2 The Impact of TTR on Repurchase

I conduct a similar analysis for the REPURCHASE model (Equation 2.2) to understand how a return event moderates the satisfaction-repurchase behavior link for different return times. I find that, although the magnitude of coefficients are slightly different, the findings for the middle three groups (returns that occur between day 1 and day 45) demonstrate similar results to the main findings. Therefore, to improve readability, I report the aggregated findings for the middle three groups along with 0-day returners and late returners (TTR>45 days) in Table 2.6.

Table 2.6: Estimation results for the repurchase model for different TTR groups

TTR	Key Independent Variables				
	SATISFACTION	RETURN		SATISxRET	
0-day	0.44*** (0.051)	1.78	(0.879)	-0.36	(0.366)
1-45 days	0.41*** (0.058)	4.10***	(0.060)	-0.48***	(0.124)
>45	0.41*** (0.056)	0.97†	(0.365)	0.23	(0.266)

The findings suggest that a return event is not associated with the repurchase behavior of a customer who returns a product on the day of the purchase (0-day). I observe that

the results for returns that occur between day 1 and day 45 are consistent with the findings from the entire dataset. Finally, I observe that while the main effects are significant, the interaction term is not significant for the last group. I illustrate the findings in Figure 2.6. The figure demonstrates the repurchase behavior of each returner group and non-returners with respect to SATISFACTION using predicted margins produced based on only significant coefficients.

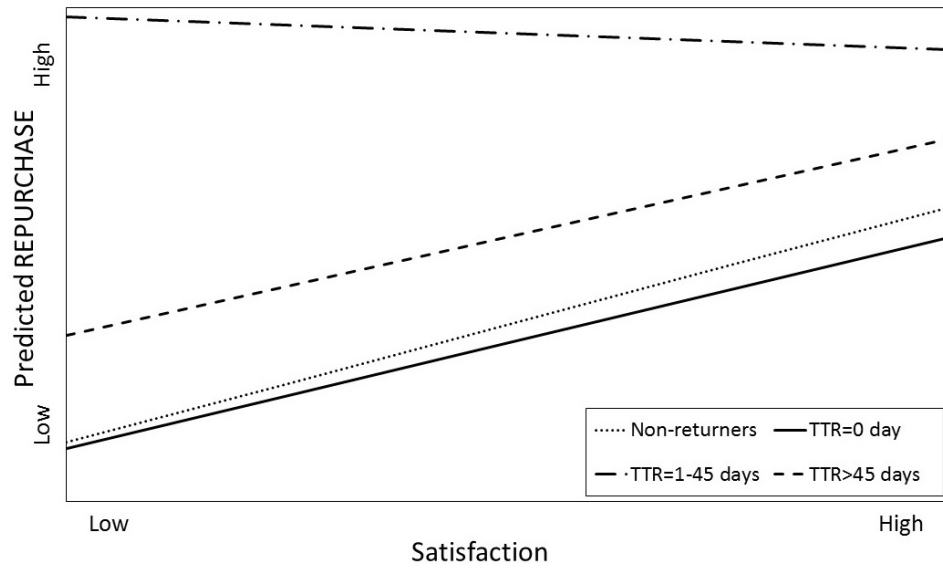


Figure 2.6: The effect of time to return on customer repurchase behavior

2.6.4 Robustness Checks

The results remain robust to several checks on regression model specifications, theoretical model constructions, sampling schemes, omitted variable issues, and alternative operationalization of dependent variables. First, I replicate the analysis using normal standard errors and robust standard errors and find consistent results. Second, to justify the theoretical U-shape relationship between COMPETENCE and RETURN in Equation 2.1, I estimate linear, cubic, and quartic models and compare each to the quadratic model using Akaike

Information Criterion (AIC) and Bayesian Information Criterion (BIC). AIC and BIC for different models indicate that the theoretical quadratic model fits best to data.

Third, I estimate each model 30 times using a different sample of 100,000 non-respondents along with 73,598 respondents for each time. Fourth, I use different sample sizes for non-respondents including 50,000, 75,000, 200,000, and 400,000. I find that neither the sample size nor the sample itself change the findings. Fifth, the rich set of control variables I use in the analysis mitigates the concerns due to omitted variable bias (Davidson and MacKinnon, 1993).

Finally, I operationalize REPURCHASE in two alternative ways. I define it (1) as the number of items purchased within a year and (2) as the number of purchase visits (transactions) made within a year. Both constructs necessitate the use of a count regression model such as Poisson and Negative Binomial regressions (Greene, 2012). The difference between these two models is the assumption of equality of the conditional mean and variance of the dependent variable. Even though the summary statistics of these two variables indicate that a Negative Binomial model would be a better fit due to the lack of the equidispersion assumption, I estimate Equation 2.2 using both Poisson regression model and Negative Binomial regression model for alternative REPURCHASE constructs. I find that alternative operationalizations of REPURCHASE do not change the insights, providing additional support to my framework.

2.7 Discussion and Conclusion

This study contributes to the understanding of consumer return behavior by examining the association between in-store customer experience during a purchase and a subsequent return and repurchase behavior. While the extant literature draws attention to varying return rates across industries due to several sector-specific factors, I show that return rates across stores within the same company, where sector-specific differences do not exist, can vary significantly as well. This study is among the first studies to empirically examine this variation with respect to product quality, service quality, and customer satisfaction. I also provide empirical evidence that a return event can actually moderate the satisfaction-

repurchase link. I further identify how a return event can moderate this link differently for different return times. Using data from a national jewelry retailer, I conduct a detailed analysis by employing a rigorous empirical approach that incorporates a sample selection model with simultaneous recursive equation models. The unique and rich data set allows me to tie *customer perceptions* about a purchase experience to the *actual return and repurchase behaviors*. I now interpret the findings and provide practical managerial insights.

2.7.1 Return Prevention

Considering that managers today are actively seeking return prevention tactics (Douthitt et al., 2011; Anonymous, 2015 (accessed Apr 01, 2015), this study demonstrates managerially relevant findings for any firm that wants to better manage consumer returns. Theoretically, I identify satisfaction with a purchase, product quality, and service quality as factors that influence and help to explain customer return behavior. The findings suggest that satisfaction during a purchase event reduces returns. Customer satisfaction is an important performance measure for retail stores as it is related to future sales. The results add additional importance to customer satisfaction since high customer satisfaction also indicates lower return rates for stores. Among the key product and service quality elements, I find that product quality and salesperson competence have more impact on returns than store environment whereas salesperson helpfulness does not influence returns.

With respect to product quality, I observe that when customers perceive high product quality, they are less likely to return an item. While many papers discuss that increased product quality should reduce consumer returns, this study is the first that empirically demonstrates this relationship. One way to ensure high perceived product quality is to include high quality products in a firm's product assortment. By doing so, one would expect that when all stores within a company carry very similar assortments, as is the case in Diamond, the product quality should not contribute to the variation in returns across stores. Yet, surprisingly, I observe that a customer's perception about product quality contributes significantly to the variation in returns. This indicates that, in addition to offering high quality products, what is equally likely to ensure highly perceived product quality is making

customers aware of the actual quality of products. Otherwise, firms who offer high quality products with the belief that returns due to quality should be low can still face high returns.

With respect to service quality, I show that high salesperson competence might be associated with decreased returns up to a threshold. After the threshold, an increase in a customer's perception about the competence may *increases* returns (i.e. U-shaped relationship). While the first effect of salesperson competence is expected, the latter impact is counterintuitive and surprising given the common belief in consumer returns literature that high salesperson competence should reduces returns (Ferguson et al., 2006; Ofek et al., 2011). To further understand the underlying reason for this finding, I obtain additional documents from Diamond regarding its salespeople training. I find that as expected, the training aims to increase product knowledge and emphasizes the importance of (1) understanding customer needs by asking the right questions and (2) providing detailed product information to match customers with the right product. However, I also find that the training requires salespeople to *excite* customers by emphasizing multiple product attributes and by *romancing* the product through making a connection between the customer and the product as well. Therefore, I conjecture that excessively high provision of information and exciting customers with the product may unnecessarily increase customer expectations beyond what the product can actually deliver. This, in turn, may reduce the postpurchase perceived valuation and lead to a subsequent return. To the best of my knowledge, this is the first empirical finding that establishes how a salesperson who provides information to reduce product valuation uncertainty may indeed induce a subsequent return by overselling a product if the information unnecessarily increases expectations from the product.

Interestingly, for the Diamond store environment, I find that returns are more likely to occur when customers perceive a store's environment to be nice and comfortable. Intuitively, one would think that setting an environment to better display products should potentially increase the likelihood of product fit, and therefore, reduce returns. As is typical in any jewelry store, Diamond stores display products in cases that are equipped with advanced lighting to ensure that jewelries and diamonds shine and sparkle. I believe that while this

specific setting increases the attractiveness of a product, as with the salesperson competence, it is also likely to increase a customer's expectation about the appearance of the product. When the customer leaves the store and puts on the jewelry or diamond under normal lighting, it may no longer look the way it looked in the store. Therefore, the customer's expectation about the product appearance is not met, resulting in a return. It is possible to see similar situations in different retail contexts. For instance, a customer who purchases an ultra HD curved TV based on the screen quality displayed in a store may be disappointed later if she does not have the ultra HD broadcast at home and uses the TV with a traditional broadcast. Similarly, apparel purchased based on how it looks on a mannequin or a furniture set purchased based on how it looks in a showroom where there is special lighting and wide space are potential examples that may result in subsequent returns due to the mismatch between the store environment and the home or daily use environment.

In a post hoc analysis, I group returns based on the time between the original purchase and returns (time to return) and assess how customer experience influences returns that occur at different times. I find that, except for the store environment, service quality and product quality do not explain return behaviors of customers who return their products on the day of their purchase (0-day). Note that Diamond stores are located in shopping malls and competition between jewelry retailers are typically high in malls. Therefore, I believe that 0-day returners are potentially customers who do comparison shopping. These customers potentially value the price more than the service quality offered in-store. Hence, even if the customers are satisfied with their in-store experiences, they may still return their purchases so long as they find a better price for the quality they seek. I observe that store environment indeed reduces 0-day returns, implying that customers who do comparison-shopping associate store environment with the product quality. For returns that occur at other times, I find that perceived product quality is an ultimate factor that explains return behaviors. The main findings hold for customers who return their products within two weeks. I also observe that satisfaction with a purchase experience does not influence return behaviors of customers who return their products beyond two weeks.

2.7.2 The Impact of Returns on Repurchase

Given the increasing marketplace claims that suggest customers will shop more often if they experience a positive return, this study examines how customer satisfaction with a purchase influences repurchase behavior for two different groups: returners and non-returners. Theoretically, I contribute to the literature by introducing a return event as another factor that moderates the link between satisfaction and repurchase behavior. The findings suggest that a return event is likely to increase customer repurchase behavior. However, the impact of a return event on repurchase behavior dependd on a customer's satisfaction level during a purchase. Satisfied customers are typically loyal and demonstrate a certain level of repurchase behavior. For these customers, a return event further increases their repurchase behavior. For dissatisfied customers, I observe that after a dissatisfactory shopping experience, customers almost stop shopping with the firm. However, this study demonstrates that a return event turns these customers into loyal ones. This implies that a return event is critical for retailers to regain a dissatisfied customers that would otherwise be lost. It also represents another point of the retailers service offering that is highly valued by customers.

Finally, in the post hoc analysis, I compared repurchase behavior of customers who return their products at different return epochs. Evidently, the repurchase behavior of zero-day returners is not different from the repurchase behavior of non-returners, implying that a return event does not influence the repurchase behavior of comparison-shopping customers. I observe that the main findings are consistent for customers who return their products between day one and day 45 after the initial purchase. As for the returns that occur beyond 45 days, Diamond store managers note that many of these late returns arise from customers who appear to act opportunistically. That is, these customers commonly return expensive items at the end of the return period. In contrast to the main findings, I observe that the effect of a return event on the repurchase behavior of these late returners does not vary with their satisfaction level. This is expected since, regardless of the level of satisfaction with the purchase, these late returners will continue to purchase from the same retailer so long as they are allowed to return.

2.7.3 *Managerial Implications*

The findings provide actionable ideas for retail managers who seek to prevent consumer returns or otherwise maximize value from the return process. This study shows that product quality, service quality, and customer satisfaction are key factors for returns management. Ensuring customer satisfaction during a purchase event reduces the likelihood of a subsequent return. Customer satisfaction is critical for retail managers as it not only reduces returns, but more importantly, increases future sales. The link to future sales, however, is not always recognized. This is particularly so for store managers and salespeople that work on commission. Their income incentive has them focused on getting the sale today, without regard to long-term customer satisfaction. My observations of salespeople at Diamond indicate that they often rely on the return policy as a sales mechanism, perhaps as much as customers rely on the return policy as an insurance against dissatisfaction. It is far easier for salespeople to rightfully inform customers that they can return a product if they are not 100% satisfied than to ensure customers that they will be 100% satisfied by finding the right product match in the first place. This practice arises even though it leads to lower customer satisfaction and higher returns, and in turn, actually lower commissions for salespeople. Not only due returns increase, but the value of the customer relationship declines. The findings suggest that retailers should provide an incentive that balances the long-term relationship with the short-term sale. Indeed, a long-term profitable customer relationship and successful short-term sales are not incompatible as I clearly demonstrate that increasing customer satisfaction reduces returns. Managers can balance these long-term and short-term objectives by tying compensation to a quantifiable measure of satisfaction (e.g. customer satisfaction surveys).

From the product side, returns are less likely to occur when customers perceive products to be of high quality. It is not just that retailers need to supply the requisite quality, but that customers *perceive* it. My experience with Diamond indicates that although the company consistently provides high quality throughout its stores, customer perceptions of quality vary significantly. This variation arises between stores and over time, although the same

products are offered. I conjecture that the perception of product quality may vary due to ignorance and lack of experience. If customers do not see it, know it, or understand it, they will not *perceive* it. In essence, for a variety of products, particularly technology products, customers require an education. Without it, customers may perceive low quality when it does not exist or otherwise rely on inaccurate or improper quality cues. For jewelry, it is clear that an education in diamond quality is a prerequisite for understanding what constitutes high quality. Diamond quality is determined by what are known as the 4Cs: carat, color, clarity, and, cut. While some customers may not be aware of these factors at all, other customers may not understand how the 4Cs work together to determine a diamond's overall quality. A jewelry retailer that offers high quality diamonds can prevent returns due to low perceived quality by educating its customers about the 4Cs during a purchase event.

From the service delivery side, a competent salesperson who can identify a customer's needs and provide product information to meet those needs will potentially reduce the customer's uncertainty about the product and therefore, prevent a future return. However, over-selling a product or providing too much information can unnecessarily increase a customer's expectations from the product and potentially result in a return due to a disconfirmation of expectations. Retailers typically increase salesperson competence by investing in training. While training investments are likely to increase salesperson competence overall, this study demonstrates that this increase may result in undesired consequences when returns are not considered. Therefore, retailers should design their training modules to ensure that salespeople set reasonable expectations that actually can be met by the product. In addition, I find that a store environment that increases expectations from products, increases returns as well. To prevent returns, retailers should carefully design their store environment so that the product appears and functions approximately the same way as it would appear and function outside the store during the customer use after the purchase.

While I provide actionable prescriptions for return prevention, I also note that a return event can actually lead to an enhanced customer relationship. I demonstrate that customers highly value a retailer's return policy and increase their repurchase behavior after they

experience a return. More interestingly, I show that during a return event, retailers can regain a dissatisfied customer who otherwise would be lost. These findings suggest that retailers should actively track customer satisfaction and, in fact, should persuade dissatisfied customers to return their initial purchases. In these cases, the results demonstrate that the short-term loss of a return is more than compensated through an increase in future purchase behavior.

Finally, in the present era of big data and predictive data analytics, many major retailers have access to transaction data and survey data similar to the data I use in my research. This study illustrates how managers can use these data to analyze their operational performances from the customer perspective and to identify return drivers and customer returner segments that can potentially be improved.

2.7.4 Limitations and Future Research

While this study provides fruitful findings for retailers, it has certain limitations. Even though the data include transactions made by over a million customers and represent a very wide range of purchase and return behaviors, this study is based on observations from a single firm. While the data fit my goal of explaining the return rate variation across stores within a single company, I am not able to compare the results to another retail setting with different product categories. Future research should examine how return behavior across stores within a single company differs in different retail contexts. Second, I am not able to identify the underlying reason behind a return. Many organizations, including Diamond, ask for and record verbal feedback on why customers return an item, yet such feedback can be fraught with its own data issues due to lack of truthfulness, customer opportunism, and error-prone textual recording of the feedback. Even though I conduct the analysis after eliminating returns due to a repair transaction or a trade-in transaction, future research that categorizes returns based on the reason such as defect, buyer's remorse, or mismatch would potentially reveal further details in return prevention. Third, I am not able to identify why a return increases repurchase behavior. It is not clear whether the satisfaction with the return service or the returning option itself leads to increased repurchase behavior. Future research

can also shed light on *return event* as I do on purchase event.

3. OPEN-BOX RETURNS: TRASH OR TREASURE TROVE?

3.1 Introduction

Retailers are inundated with product returns and the situation has only been exacerbated in recent years with the tremendous growth of remote purchases through the Internet. Even brick-and-mortar establishments often must contend with a veritable flood of returns. The competitive dynamics of the marketplace, combined with ever-demanding consumers, means product returns are now business-as-usual. Consider that the annual value of returned goods in U.S. retailing increased from \$188.9 billion in 2007 to \$267.3 billion in 2013 (NRF, 2007, 2013). With no end in sight, let alone a decrease in their volume, retailers must contend with how best to handle the returns they accumulate. The answer is not trivial, nor are the consequences insignificant. In 2007 alone, the U.S. electronic industry spent an estimated \$13.8 billion to repackage and resell returned merchandise (Lawton, 2008). Indeed, returns can reduce profits by as much as 35% (Hewitt, 2008).

One common option for retailers to handle the returns they collect is to salvage the returns by selling them to third party liquidators at a deep discount. However, this is a costly method since retailers recoup only 10%-20% of the original value of returned products (Stock et al., 2006). For instance, Best Buy, a consumer electronics company with around a 10% return rate, lost about \$400 million annually in the past by selling returned products to third-party liquidators (Lee, 2014 (accessed May 30, 2014)). Therefore, retailers often pursue other options for handling returns. One such option is to send product returns back to the manufacturer for credit. Retailers may also attempt to remarket those products themselves. In fact, some retailers have even developed their own secondary retail channels to remarket the returns from their primary branded outlets. Nordstrom Rack and other outlet stores are prime examples of such remarketing efforts. Recycling and donating returns to charity are some other, less common alternatives for disposing returns.

Increasingly, retailers are turning to selling returns in their own primary outlets, side-

by-side with their new product offerings. By use of the term side-by-side, I mean that both returns and new products are available for sale to customers in stores at the same time. An industry report by UPS indicates that companies that process returns internally and resell them in a timely manner save more and earn more from their returned products than those that liquidate returns through a secondary market (Greve and Davis, 2012). Even so, it remains unclear how and under what conditions a retail strategy of selling internally, as opposed to third party liquidators, should be implemented. This study addresses this issue.

A complicating factor for managing returns is their condition. Generally, I can distinguish two types of returns: *closed-box* and *open-box*. Closed-box returns, by definition, means that the items have not been opened by customers and are in good-as-new condition, as if they have never been sold in the first place. In essence, closed-box returns are indistinguishable from new products. Open-box returns, in contrast, are not good as new. Often, the packaging is torn, items have not been repackaged correctly, or there may exist some other cosmetic issues or slight imperfections. Selling these returns as new may create complications. In the past, Wal-Mart Stores Inc. and Toys 'R' Us Inc. were accused of routinely misrepresenting and selling returned products as new (WSJ, 1993). Indeed, it is illegal to sell open-box products as new without proper disclosure. Moreover, state-specific regulations might restrict selling returned products as new. For instance, at a national jewelry retailer chain that I study, a returned watch cannot be sold as new in certain states, regardless of its condition.

Still, retailers often sell open-box products side-by-side with new products, albeit at a lower price than the new product price. As part of its Renew Blue strategy, Best Buy set aside an area in stores for just this purpose. By doing so, the company significantly reduced its losses due to liquidating returns in the third quarter of fiscal year 2013. The company also plans to move all its online open-box products from its secondary website called CowBoom to its main BestBuy website over time (Seitz, 2013 (accessed May 30, 2014)). Similarly, many consumer electronics retailers including Dell, Amazon.com, Newegg.com, and Walmart, sell some of their open-box products at a discounted price along with their new products. Clearly, selling product returns along with new products is nothing new. However, many other

retailers either abstain completely from this practice or limit it with certain products. An often-heard concern is that open-box products cannibalize sales of new products. *When and under what conditions is the strategy of selling returns as open-box products better than the strategy of salvaging them? What is the impact of cannibalization due to open-box products on new product sales and profitability?*

At the policy level, a host of fundamental questions arise that, to the extent I am aware, have not been addressed in the literature. In particular, I am interested in answering managerial questions related to product price, restocking fee, and order quantity since these are the key levers that affect a firm's ability to operationally match supply with demand. Even when I look to industry for guidance on policy, the answers to operational level questions are not clear. First, consider the issue of product price. I can observe a variety of different pricing strategies for open-box products. Some retailers apply very small discounts, while others offer larger savings of up to 25% (Consumer-Reports, 2008 (accessed Jun 27, 2014)). A discounted price will attract more price-sensitive customers who normally would not purchase a new version of the same product. At the same time, open-box products at low prices may cannibalize part of new product demand. *What is the right pricing strategy to sell open-box products vis-à-vis new products?*

The second managerial lever, a restocking fee, has both supply-side and demand-side effects, the combined effects of which are not clear. Common wisdom suggests that retailers can influence demand through return policies by applying a restocking fee. A lenient return policy with a low restocking fee is likely to increase demand (Ketzenberg and Zuidwijk, 2009; Akcay et al., 2013). It is also likely to reduce profits due to the increased cost of handling returns (Hewitt, 2008). Indeed, it is a question whether or not the benefit of higher demand due to a lenient return policy outweighs the cost of higher returns. As with pricing of open-box products, when I look to industry for guidance on policy, I observe a wide range of restocking fees. A 2005 survey indicates that 44% of retailers charge restocking fees on returns (Akcay et al., 2013), and these fees can be significant. For returned electronic goods, Target and NewEgg.com charge customers a 15% restocking fee and Amazon.com

and RitzCamera.com apply a restocking fee of up to 25%. *Under what conditions should retailers charge a restocking fee for returns and by what amount? How does the restocking fee influence the sales price of open-box products and if so by how much?*

The third managerial lever with regard to product returns is the order quantity for new product inventory. In essence, the pool of returned products may serve as another potential source of supply. Since returns can be resold to satisfy demand, retailers may require fewer new products. This issue is especially crucial for products that have short selling seasons and high return rates like apparel. *Should retailers alter their order quantities for new products in anticipation of product returns and if so by how much?* This study aims to answer these and similar questions as they relate to selling both new and returned products together.

This paper compares two different strategies for handling returns: salvaging returns or selling them as open-box products along with new products. I model the problem for a retailer that sells a single product, charges customers a restocking fee for returns, and segments the market for new and open-box products. Demands from both segments are satisfied by selling new and open-box products side-by-side over a single selling season. The operational decisions of interest are the price of open-box products, the restocking fee for returns, and the order quantity for new product. The retailer has a single ordering opportunity before the season starts. Customers are heterogenous in their valuations of new and open-box products and realize their product fit after purchase.

The modeling contribution of this paper to the literature is three-fold. First, I address the strategy of reselling returns during the selling season when there is imperfect substitution between new and returned products. Second, I distinguish product returns based on their condition (i.e. closed-box vs. open-box) and consider a different reselling option for each condition. Finally, I model a customer's sensitivity to a retailer's return policy as a determinant for her utility from purchasing a new product. The last contribution is particularly meaningful as it leads to important and interesting insights for managers.

I summarize the key findings as follows. First, when at least some customers in the market prefer open-box products to new products, selling returns as open-box is always a

more profitable strategy than simply salvaging them. This arises even though open-box products cannibalize demand for new products. Second, retailers may increase their overall market share by selling returns as open-box if customers are insensitive to a retailer’s return policy. If customers are indeed sensitive, retailers should use a generous policy to increase demand for new products and charge premium prices. There are some unexpected results. For instance, higher return rates do not necessarily lead to a decrease in profit. Moreover, when product returns increase, retailers do not need to decrease the price to sell all open-box products. The intuition is that restricting return policy to prevent returns will increase demand for open-box products.

I organize the rest of this paper as follows: In §3.2, I review the relevant literature. In §3.3, I introduce the modeling framework and discuss my assumptions. In §3.4, I define the model and derive analytical insights. In §3.5, I discuss several practical extensions to the model. Finally, §3.6 summarizes the research and provides future research directions.

3.2 Literature Review

This study draws upon three separate streams within the overall product returns literature in closed loop supply chain management: return policy, inventory management, and remanufacturing. I review each stream and position this work with respect to them.

3.2.1 *Return Policy*

A return policy should clearly indicate (1) the refund amount paid (or the restocking fee charged) to a customer for returning a product, (2) the time period in which customers are allowed to return a product, and (3) the level of hassle that identifies the restrictions imposed on customers who return a product. Despite a few studies that address the time period (Ulku et al., 2013) and the level of hassle (Davis et al., 1998), most literature in this stream study return policies with respect to the refund amount.

Return policies differ in their leniency and range from a no return policy to a full return policy. In a no return policy, returns are not allowed. A full return policy allows customers to be fully reimbursed for the returned products if they are not satisfied with their purchase.

Any policy between the two is called a partial return policy and that is the policy I address in this study. With a partial return policy, retailers charge a restocking fee for each return. Early papers on partial return policies investigate the use of a restocking fee to avoid inappropriate returns from customers who have no intention of keeping the product in the first place (Hess et al., 1996; Chu et al., 1998). Subsequent papers study partial return policies within the context of quality and discuss how such policies can be used to signal product quality (Mukhopadhyay and Setaputra, 2007; Hsiao and Chen, 2012; Li et al., 2013).

Motivated by the marketing literature, a few studies have addressed return policies for segmented markets. Among them, Yalabik et al. (2005) show that the refund amount will be less than the product price when both high-valued and low-valued segments are allowed to return a product. However, if sales are final for one segment, then the retailer may offer a refund greater than the product price for the other segment. Swinney (2011) studies a firm that adopts a quick response production strategy and sells to two different segments: strategic (forward-looking) and non-strategic (myopic) customers. He shows that, under a partial return policy, the firm's profit and the value of quick response are greater with strategic customers than non-strategic customers when a return is less costly for customers than for the firm. Shulman et al. (2009) study the optimal restocking fee for a horizontally segmented market when customers have a choice among multiple products. They demonstrate that multiple products enable a retailer to convert some returns into product exchanges. This is one way to recoup the cost of returned products. Hence, the retailer provides a refund greater than the salvage value. Shulman et al. (2011) extend the literature for horizontal segmentation under competition. They show that the optimal restocking fee is higher under competition than when the retailer is a monopolist. In this case, a high restocking fee is designed to prevent customers from returning a product and subsequently buying from a competitor.

This stream of literature addresses return policies without the consideration of inventory management. I fill this gap by addressing the inventory order quantity decision along with a partial return policy for a segmented market.

3.2.2 *Inventory Management*

Returned products may enable retailers to satisfy demand more than once with the same unit of inventory. Therefore, the order quantity for new product can be less when there are returns. From a modeling perspective, I see two common assumptions in the literature with respect to return handling: (1) retailers restock returned products and sell them as new (also known as the perfect substitution assumption) and (2) they do nothing specific to remarket returns themselves, but rather simply obtain a salvage value from selling them to a secondary market or sending them back to manufacturers.

In a seminal piece in this area, Vlachos and Dekker (2003) introduce a single period model with resalable returns and derive an optimal order quantity for a retailer under the perfect substitution assumption. Later, Mostard and Teunter (2006) extend this model by relaxing some restrictive assumptions - most notably that returned products can be resold only once and that a fixed percentage of sold products is returned and resalable. They show that the order quantity decision is different when a returned product is resalable more than once. In both papers, the demand and the price of the product are exogenous. In a two period model, Ketzenberg and Zuidwijk (2009) derive a model with resalable returns to determine the optimal order quantity for a retailer that sells to customers who are sensitive to both price and return policy. Chen and Bell (2009) extend the literature by introducing a multi-period model for a retailer that sells to price sensitive customers and modifies his pricing and ordering decisions in time to respond to customer returns.

Largely motivated by the marketing literature, recent studies consider the behavioral aspects of consumer returns. A typical assumption is that customers face valuation uncertainty and realize their true valuation only after purchase. Within this context, Su (2009) studies a newsvendor model under a full return policy and a partial return policy. He shows that the retailer's profit and optimal order quantity are higher under the partial return policy than they are under the full return policy. In both models, he assumes that returns are not resold, but are simply salvaged.

To the best of my knowledge, Akcay et al. (2013) is the closest paper to my own. They

extend the literature by introducing the option of selling returned products as open-box at a discounted price from the new product price. The authors show that this approach enables the retailer to increase the refund amount and the price of the new product compared to doing nothing and salvaging all returns. The open-box products are sold to satisfy demand for the new product only if the new product inventory is depleted. The implicit assumption is that open-box products are never offered to customers along with new products at the same time. In contrast, I allow the retailer to sell open-box and new products side-by-side.

3.2.3 Remanufacturing

Remanufacturing is a production strategy to recover the residual value of returned products. Remanufacturing involves collecting used products that are at or near their end-of-life, reusing parts that are functioning well, and replacing worn-out parts with new ones. Souza (2013) provides a detailed and recent review of the area. Here, I am limiting my scope of the remanufacturing literature to include only those papers that (1) address a manufacturer who sells new and remanufactured products simultaneously and (2) consider behavioral aspects of product valuation. The planning horizon generally involves two or more periods. It is common that the manufacturer only produces new products in the first period, but has the option to make new and remanufactured products in subsequent periods. In this context, remanufactured products are produced from products returned in prior periods. Even though the context is different, the second and the subsequent periods of a remanufacturing problem are similar to the single period problem. They are similar in the sense that in a remanufacturing (our) problem, (1) returned products are sold as remanufactured (sold as open-box), (2) remanufactured (open-box) products and new products are offered side-by-side, and (3) remanufactured (open-box) products are valued less than new products by customers (Ferguson and Toktay, 2006; Akcay et al., 2013).

Early papers in remanufacturing assume that there is perfect substitution between a new product and its remanufactured counterpart such that remanufactured units are sold good as new (Toktay et al., 2000). More recent papers relax this assumption (Debo et al., 2005; Ferguson and Toktay, 2006; Atasu et al., 2008b) and this paper is comparable to

this literature. From a modeling perspective, there are two key aspects of these papers that are relevant to my own study. First, they all assume that the demands for new and remanufactured products are functions of prices. Second, demands are deterministic. While I also examine the case of deterministic demand, I extend my analysis to the stochastic case. Another key differentiating aspect of my model is that new and open-box demands are functions of both prices and refund amount.

3.3 Model Framework

I consider a retailer that sells a single product to customers under a partial return policy. There are three decisions: the price for open-box product, the refund amount paid for returned product, and the order quantity for new product. The price for new product is exogenously determined. This represents the case in which retailers sell new products at the manufacturer suggested retail price (MSRP). This is a common pricing strategy observed in consumer electronics industry when a new product is introduced to the market due to either high level of competition or policies such as price matching or MSRP.

I assume a single selling season. Before the beginning of the season, the retailer purchases an initial stock of Q units from her supplier at unit cost c , sells new products at the MSRP p_n , and sells open-box products at unit price p_o . Any unsold units remaining at the end of the season, either new or returned, are salvaged at a price s per unit. I assume that $s < c$ so that it is not practical to purposely stock for salvage.

3.3.1 Returns Process and Restocking

Customers return products if they are not satisfied. For each return, the retailer reimburses the customer a refund amount r , where $s \leq r \leq p_n$. I assume $r \geq s$; otherwise, customers would salvage products by themselves rather than returning them to the retailer. Craigslist and eBay are illustrative examples of self-salvaging. Note that $p_n - r$ represents a restocking fee. A returned product can be either closed-box with a probability of α or open-box with a probability of $1 - \alpha$. I do not consider defective returns since they typically account for a small portion of all returns and would add unnecessary complexity to the

model (Douthit et al., 2011).

I assume that both open-box and closed-box returns are offered side-by-side with new products for the entire season. I observe that in practice, a majority of all returns occur within a few days after purchase. For example, 36% of all returns occur within two days after purchase at a national jewelry retailer chain I study. Given that a selling season usually lasts an extended number of weeks, it is reasonable to assume that open-box and new products are sold simultaneously over the entire length of the selling season.

Closed-box returns are indistinguishable from new products. Hence, they are sold at the same price p_n . I assume that the cost of restocking returned products is negligible. Typically, restocking is one of many responsibilities of store employees and they are not paid an additional amount for such a task. For instance, Best Buy's Geek Squad team is responsible for assessing the functionality of a returned product before restocking, as well as customer services such as consultation, installation and setup, repair, trade-in, etc. I also assume that sales of all open-box products are final; there is no refund offered for open-box products. This too is common in practice (e.g. Newegg.com and RitzCamera.com). Note that a return increases either the net inventory of open-box returns (if it is open-box) or the net inventory of new products (if it is closed-box).

3.3.2 Consumer Behavior and Choice Process

I model three types of consumer behavior: purchase behavior, return behavior, and product valuation behavior. These behaviors are explained by utility theory. Prior to a purchase, customers have an expectation about the value of a product. If the expected value is greater than the product price, customers purchase the product since the net utility from purchasing is greater than zero. A customer obtains zero utility if no product is purchased. Customers realize their valuation after evaluating their product fit, which occurs only after purchase. A customer gets zero utility if the product fails to meet expectations and this occurs with a probability of λ . In this case, customers will return the product so long as there is a positive refund amount. Hereafter, when I use the term valuation, I refer to the expected valuation.

Open-box products are attractive to price-sensitive customers who are looking to pay less for high quality products (Lee, 2014 (accessed May 30, 2014)). Similar to Akcay et al. (2013), I assume that consumers value open-box products less than new products since they have been opened and probably used by others. I address heterogenous customers who are differentiated by an intrinsic valuation parameter V for a unit of new product and assume it to be uniformly distributed on the standard Hotelling line between 0 and 1. Each customer's valuation for an open-box product is a fraction β of his valuation for the new product. A customer's value for an open-box product is βv , where $0 < \beta < 1$. Note that $\beta = 1$ implies that an open-box product is a perfect substitute for a new product. To avoid triviality, I assume $\beta v > s$; otherwise, the retailer would purposely salvage all open-box returns rather than attempting to sell them. I normalize the size of the market to one.

A return policy heavily influences a customer's purchase decision (Hsiao and Chen, 2012), and therefore, demand (Mukhopadhyay and Setoputro, 2005). A 2014 consumer survey administered by UPS indicates that 82% of respondents would complete a sale if they could return the item for free, whereas only 20% would purchase if returns are not allowed (UPS, 2014). To model this behavior, I assume that a generous return policy, represented by a high value of r , will increase product valuation and, therefore, generate higher demand. A one unit increase in r increases the product valuation by γr , where $0 < \gamma \leq 1$. Here, γ is a constant that represents consumer sensitivity to the refund amount.

Customers are risk neutral and make their decisions based on the prices and the refund amount to maximize their expected utility. Therefore, customers will purchase the product that provides the highest utility, so long as it is available. If it is not available, I assume that customers do not consider the alternative product and leave without a purchase. I explore product substitutability as an extension later. I ignore opportunistic behavior and assume that all returns are legitimate. Moreover, I do not separately consider the cost of returning for the customer since it can be considered as part of the term γr in the product valuation. For instance, a customer with a high cost of returning will likely have a lower γ than a customer with a low cost of returning.

The order of events is given as follows. (1) Before the season starts, the retailer determines the refund amount r , the price of the open-box return p_o , and the initial stock Q to maximize her expected profit. (2) Market demands for both types of product (new and open-box) are realized. Each arriving customer makes a purchase decision (buy or not) and a product choice (new vs. open-box) based on his/her valuation and product availability. (3) Customers who purchased a product realize their individual valuations. If a customer has purchased a new product, he/she decides to keep it or return it for the refund r . Finally, (4) the retailer salvages all leftover products at the end of the selling season. I summarize the notation in Table 3.1.

Table 3.1: Table of notation

Symbol	Definition	Symbol	Definition
p_n	new product price	p_o	open-box product price
r	refund amount	c	procurement cost
s	salvage value	v	customer valuation for new products
β	valuation discount factor	γ	refund amount sensitivity
λ	probability that a product is returned	α	fraction of returns that are closed-box
d_n	new product demand	d_o	open-box product demand
Q	order quantity		

3.3.3 Demand Functions

I derive the demand functions of new products and open-box products directly from consumer utility functions, as is common in the closed-loop supply chain literature (Debo et al., 2005; Ferguson and Toktay, 2006; Atasu et al., 2008a). The utilities from purchasing a new product and an open-box product are $U_n = v + \gamma r - p_n$ and $U_o = \beta v - p_o$, respectively. When a customer has an option to buy either a new product or an open-box product, she makes her decision based on the comparison of her utilities for both products. All customers whose valuations satisfy $v + \gamma r - p_n \geq 0$ would consider buying a new product. The customer with valuation $v^n = p_n - \gamma r$ is indifferent to buying a new product or not buying at all. Similarly, the customer with valuation $v^o = \frac{p_o}{\beta}$ is indifferent to buying an open-box product

or not buying at all. Finally, a customer with valuation $v^{no} = \frac{p_n - p_o - \gamma r}{1 - \beta}$ is indifferent between new and open-box products, and if the valuation exceeds this, she prefers the new product. I demonstrate the three points of indifference in Figure 3.1 for two different cases.

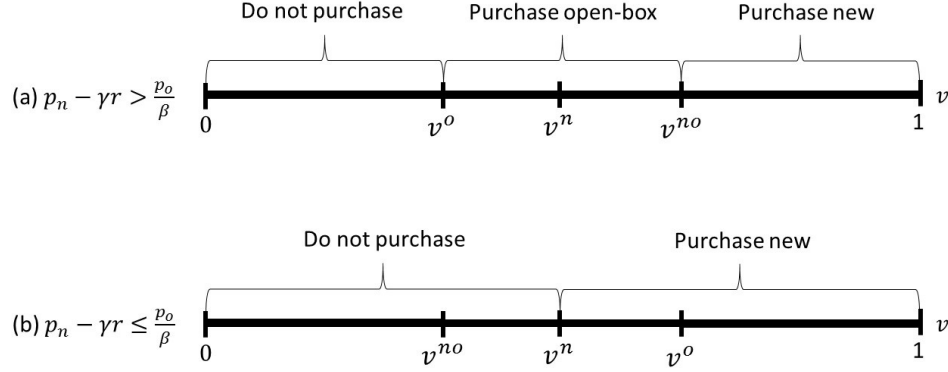


Figure 3.1: Demand for both products

When $v^n > v^o$ (or $p_n - \gamma r > \frac{p_o}{\beta}$), it can be readily shown that $v^{no} > v^n > v^o$. In this case, as illustrated in Figure 3.1(a), all customers with valuation in the interval $[v^{no}, 1]$ prefer to buy a new product and all those in the interval $[v^o, v^{no}]$ prefer to buy an open-box product. Customers whose valuations are in $[0, v^o]$ do not buy anything. When $v^n \leq v^o$ (or $p_n - \gamma r \leq \frac{p_o}{\beta}$), $v^o > v^n > v^{no}$. This implies that no customer will buy an open-box product since any customer with a positive utility for an open-box product always prefers a new product (Figure 3.1(b)). All customers whose valuations are in the interval $[v^n, 1]$ will buy a new product.

Because the customer valuation follows a uniform distribution, I can define the following piecewise-linear demand functions for new (d_n) and open-box (d_o) products:

$$d_n = \begin{cases} 1 - \frac{p_n - p_o - \gamma r}{1 - \beta} & \text{if } p_n - \gamma r > \frac{p_o}{\beta} \\ 1 - p_n + \gamma r & \text{if } p_n - \gamma r \leq \frac{p_o}{\beta} \end{cases} \quad (3.1)$$

$$d_o = \begin{cases} \frac{\beta p_n - p_o - \beta \gamma r}{\beta(1-\beta)} & \text{if } p_n - \gamma r > \frac{p_o}{\beta} \\ 0 & \text{if } p_n - \gamma r \leq \frac{p_o}{\beta} \end{cases} \quad (3.2)$$

Hereafter, I refer to the demand for new products as *new demand* and the demand for open-box products as *open-box demand*. Equations 3.1 and 3.2 imply that when $p_n - \gamma r > p_o$, any increase in the price of one product reduces the demand for that product and increases the demand for the other product. Similarly, any increase in the refund amount increases new demand and decreases open-box demand. In contrast, any increase in β shifts the demand from new products to open-box products. I also note that when $p_n - \gamma r \leq \frac{p_o}{\beta}$, the retailer can only sell new products. When $p_n - \gamma r > \frac{p_o}{\beta}$, the retailer can (1) sell both new and open-box products or (2) sell only new products. Therefore, selling only new products is always an option for the retailer regardless of model parameters. I refer to the strategy of selling only new products as the *single-product portfolio strategy* (SPPS) and to the strategy of selling both products as the *two-product portfolio strategy* (TPPS).

3.4 Model Analysis

In this section, I first introduce the retailer's objective function, provide the optimal solutions, and show a set of propositions to identify how the retailer determines her product portfolio strategy. Then, I analyze the optimal return policy for the retailer and demonstrate how the return policy changes based on the product portfolio choice. I also look at the cannibalization of new demand due to open-box products and assess the impact of it on profitability. Finally, I conduct a sensitivity analysis for the optimal decision variables.

3.4.1 Optimal Solutions and Product Portfolio Strategy

Recall that a product return is closed-box with probability of α . Since closed-box returns are sold as new, they can be returned more than once so long as they remain unopened. Following the analysis in Mostard and Teunter (2006), I assume that a product can be sold like new $(1 + \alpha\lambda + (\alpha\lambda)^2 + \dots) = \frac{1}{1-\alpha\lambda}$ times, where λ represents the probability of returning a new product. Hence, I can assume that the retailer can satisfy new demand of d_n units when she orders $Q = (1 - \alpha\lambda)d_n$ products due to closed-box returns. The retailer's objective

function is

$$\max \Pi(p_o, r, Q) = \underbrace{p_n d_n}_{\text{new sales}} - \underbrace{r \lambda d_n}_{\text{returned}} + \underbrace{p_o \min\{d_o, (1 - \alpha) \lambda d_n\}}_{\text{open-box sales}} + \underbrace{s[(1 - \alpha) \lambda d_n - d_o]^+}_{\text{not sold open-box}} - cQ \quad (3.3)$$

The first term in equation 3.3 corresponds to the revenue from the sales of new products and closed-box returns. The second term indicates the refund amount paid to customers for returned products. The third term corresponds to the revenue from open-box products. The fourth term represents the revenue from salvaging all unsold open-box products. Note that I allow the number of open-box returns to be greater than the open-box demand. This represents the case that the benefit due to increased new demand through a higher refund amount outweighs the loss due to excess open-box returns. The last term is simply the procurement cost. Maximizing the objective function with respect to p_o and r gives the optimal solution. Note that the optimal order quantity can be derived using the optimal solutions for p_o and r .

Proposition 1. *The retailer's optimal refund amount r^* , optimal open-box product price p_o^* , and resulting optimal order quantity Q^* for the SPSS and for the TPPS on the domain $\Omega = \{(d_n, d_o, \beta) : d_o \leq \lambda(1 - \alpha)d_n, 0 < \beta < \tilde{\beta} = \frac{4\lambda\gamma}{(\lambda+\gamma)^2}\}$ are summarized in Table 3.2.*

I present proofs for all propositions and technical results in Appendix C. Note that, in Proposition 1, while the optimal solutions for the SPSS hold regardless of the values of model parameters, the optimal solutions for the TPPS are only valid on the domain Ω . The domain has two restrictions. First, $d_o \leq \lambda(1 - \alpha)d_n$ corresponds to the case in which the open-box demand is less than or equal to the available open-box returns. The company I study offers its customers 6,111 different open-box products side-by-side with their new products and open-box returns account for 40% of all returns. I observe that, for only 157 SKUs, $d_o \leq \lambda(1 - \alpha)d_n$. Second, $\beta < \tilde{\beta}$ puts an upper limit on the valuation discount factor β , below which optimality is guaranteed. For instance, for all combinations of $\lambda \in (0.1, 0.4)$ and $\gamma \in (0.1, 0.4)$, I find that $\tilde{\beta} \in (0.64, 1)$. I conclude that optimal solutions exist for a broad range of relevant parameter values. I also provide a method in Appendix D to compute

Table 3.2: Optimal solutions for product portfolio strategies for a retailer

Optimal solution	SPPS
p_o^*	-
r^*	$\frac{(\lambda+\gamma)p_n - \gamma[c(1-\alpha\lambda) - s\lambda(1-\alpha)] - \lambda}{2\lambda\gamma}$
d_n^*	$1 - p_n + \gamma r^*$
d_o^*	0
Q^*	$(1 - \alpha\lambda)(1 - p_n + \gamma r^*)$
Optimal solution	TPPS
p_o^*	$\frac{\lambda\beta(1-\beta)(\lambda+\gamma) - \beta p_n(\lambda-\gamma)^2 + s\gamma[2\lambda - \beta(\lambda+\gamma)] - \beta\gamma(\lambda-\gamma)[c(1-\alpha\lambda) - s\lambda(1-\alpha)]}{4\lambda\gamma - \beta(\lambda+\gamma)^2}$
r^*	$\frac{2(\lambda+\gamma)(1-\beta)p_n - 2\lambda(1-\beta) + s(\gamma-\lambda) - [2\gamma - \beta(\lambda+\gamma)][c(1-\alpha\lambda) - s\lambda(1-\alpha)]}{4\lambda\gamma - \beta(\lambda+\gamma)^2}$
d_n^*	$1 - \frac{p_n - p_o^* - \gamma r^*}{1-\beta}$
d_o^*	$\frac{\beta p_n - p_o^* - \beta\gamma r^*}{\beta(1-\beta)}$
Q^*	$(1 - \alpha\lambda)(1 - \frac{p_n - p_o^* - \gamma r^*}{1-\beta})$

the optimal decisions when the model parameters are outside the domain Ω .

Proposition 1 establishes that an increase in new price also increases the refund amount. This result is in line with earlier literature (Hess et al., 1996; Akcay et al., 2013) and confirms that the insurance provided to the customer against a potential mismatch allows the retailer to charge a premium. Moreover, new price and open-box price are negatively correlated when the retailer follows the TPPS. Due to the complexity of the expressions in Proposition 1, further relationships between model parameters are not readily observable. Therefore, I proceed to analytically derive several insights from the model.

To begin, I find that refund sensitivity γ is a key parameter with respect to model behavior. I introduce a few thresholds for γ and demonstrate that the retailer's optimal decisions depend largely on the value of γ with respect to these thresholds. I start with the relationship between new demand and new price in the following proposition.

Proposition 2. *There exists a threshold $\tilde{\gamma} = \lambda$ for refund sensitivity such that when the sensitivity is above the threshold, new demand increases as new product price increases.*

Proposition 2 demonstrates a very counter-intuitive result. One would expect that when

the new product price increases, new demand decreases. However, I observe the opposite when $\gamma > \tilde{\gamma}$. The reason is that the new demand is a function of both p_n and r . When $\gamma > \tilde{\gamma}$, r is the primary determinant for demand. From Proposition 1, I know that r increases with an increase in p_n . Therefore, the retailer attracts more customers with a high refund amount than she loses due to a high price. Hence, the retailer uses a lenient return policy by offering a high refund amount to increase new demand while charging premium prices. Nordstrom is an illustrative example of such behavior; Nordstrom is a premium retailer with one of the the most lenient return policies in retail. When $\gamma < \tilde{\gamma}$, the price is the primary determinant for demand. Accordingly, new demand decreases with an increase in p_n .

Proposition 3. *There exists β^* such that (1) both the SPPS and the TPPS are feasible when $\beta > \beta^*$ and (2) only the SPPS is feasible when $\beta \leq \beta^*$.*

I report the expression for β^* in Appendix C. Proposition 3 indicates that the threshold level on the valuation discount factor, β , for an open-box product determines the feasibility of the product portfolio strategies. When $\beta \leq \beta^*$, there is no demand for open-box products. Personal hygiene products (e.g. electric shaver, electric toothbrush) represent one such product category. When $\beta > \beta^*$, demands for both products are strictly positive so that both strategies are feasible.

For increasingly higher values of β beyond β^* , open-box demand increases relative to new demand since the valuation difference between the two products diminishes and open-box products are offered at a discount. Indeed, open-box products increasingly cannibalize sales of new products as β increases towards one. Theoretically, when β is large enough, open-box products are so attractive relative to new products that all customers prefer the open-box product. In the model, this point occurs at $\beta = 1 - p_n + p_o + \gamma r$. For this improbable scenario, what the retailer should do is simply set p_o and r such that sales of open-box products are maximized. In this way, the market for both demands is always cleared and there is no leftover inventory. To do so, optimal solution involves solving the problem so that $d_o = \lambda(1 - \alpha)d_n$. For the analysis, I ignore this trivial and meaningless case and restrict my attention to cases where $\beta < 1 - p_n + p_o + \gamma r$.

Proposition 4. *When refund sensitivity is below (above) the threshold $\tilde{\gamma}$, the range of β over which it is optimal for the retailer to sell both new and open-box products expands (shrinks) as the new product price increases. When $p_n = \hat{p}_n$, β^* converges to $\tilde{\beta}$.*

I provide the expression for \hat{p}_n in Appendix C. Proposition 4 establishes that new product price determines the range for β over which both strategies are feasible. However, the relationship between this range and p_n is moderated by γ . I illustrate this relationship in Figure 3.2. This figure shows the change in β^* with respect to a change in p_n for a representative case. The figure clearly shows that β^* converges to $\tilde{\beta}$ when the new price is equal to the threshold \hat{p}_n . When $\gamma < \tilde{\gamma}$ ($\gamma > \tilde{\gamma}$), the retailer only sells new products if $p_n < \hat{p}_n$ ($p_n > \hat{p}_n$).

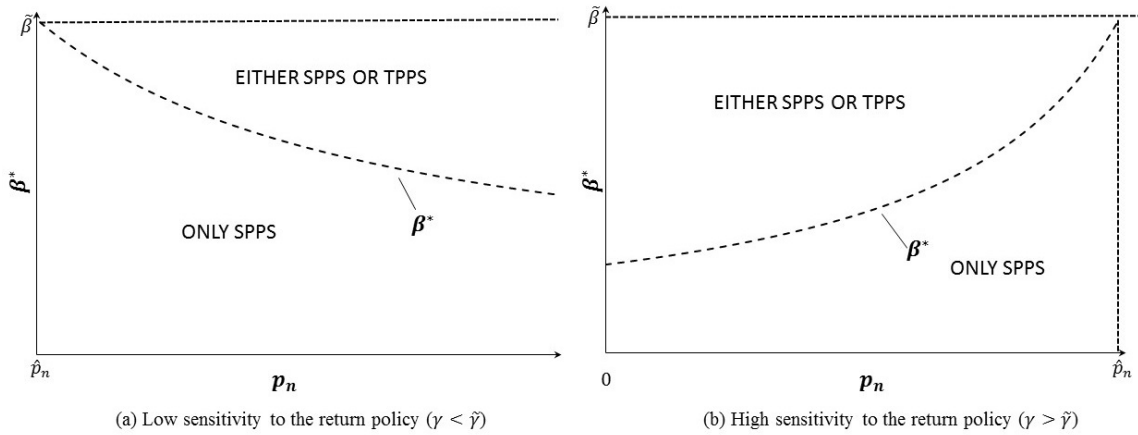


Figure 3.2: The impact of new price on retailer's product portfolio choice

When $\gamma < \tilde{\gamma}$, demand for new products decreases as p_n increases (Proposition 2). Consequently, some demand shifts from new products to open-box products. As can be seen in Figure 3.2(a), this implies that the range of valuation for which an open-box product generates positive customer utility increases as p_n increases. When $\gamma > \tilde{\gamma}$, I observe the opposite behavior. As seen in Figure 3.2(b), the range of β over which a TPPS is feasible

decreases as p_n increases. This implies that the TPPS becomes less attractive with an increase in p_n for the retailer. The intuition is that the demand shifts from open-box products to new products as r increases (due to the increase in p_n). Therefore, the range of customer valuation for which an open-box product generates positive customer utility decreases as p_n increases.

3.4.2 Optimal Return Policy

In this section, I develop insights for the retailer's optimal return policy. Note that the retailer determines the leniency of her return policy by choosing a refund amount. I also show how the optimal return policy changes based on the product portfolio choice.

Proposition 5. *There exists \bar{p}_n and $\bar{\bar{p}}_n$ (i.e. $\bar{p}_n < \bar{\bar{p}}_n$) such that the retailer offers a full refund (i.e. $r = p_n$) when $p_n \geq \bar{\bar{p}}_n$ and a partial refund (i.e. $r < p_n$) when $p_n < \bar{\bar{p}}_n$. The partial refund is equal to the salvage value s when $p_n \leq \bar{p}_n$.*

I report \bar{p}_n and $\bar{\bar{p}}_n$ in Appendix C. While Proposition 5 is in line with previous literature that suggests that retailers should charge a restocking fee (e.g. Hess et al. (1996); Su (2009); Akcay et al. (2013)) under certain conditions, it also provides theoretical support for the wide range of return policies including the full return policy that I observe in practice. In short, Proposition 5 implies that the retailer should offer a more generous return policy for premium products compared to commodity products.

The thresholds \bar{p}_n and $\bar{\bar{p}}_n$ depend on the product portfolio strategy. This implies that the refund amount also depends on the product portfolio strategy. In the next corollary, I develop insight into this dependency. I do so by comparing the optimal refund amount under the SPPS to that under the TPPS when both strategies are an option for the retailer (i.e. when $\beta > \beta^*$).

Corollary 1. *When refund sensitivity is less (greater) than $\tilde{\gamma}$, the refund amount for a TPPS is greater (less) than the refund amount for a SPPS.*

I find that a retailer should offer a more generous return policy when she sells her returns as open-box products than when she salvages them. However, Corollary 1 shows that this is

true only if refund sensitivity is low. In this case, the negative impact of curbing demand by disallowing returns for open-box products is low, implying that the opportunity to sell returns as open-box is high. In contrast, when $\gamma > \tilde{\gamma}$, this negative impact is high. Consequently, the retailer who chooses a TPPS should restrict the return policy by providing a smaller refund relative to the retailer who chooses a SPPS.

3.4.3 Cannibalization due to Open-box Products

In this section, I assess the impact of cannibalization due to open-box product sales on market share and profitability. I do so by comparing the demands and optimal profits in the SPPS to those in the TPPS when $\beta > \beta^*$. I demonstrate that cannibalization may either increase or decrease the retailer's market share depending on the refund sensitivity, γ . I also show that even with cannibalization of new products, the retailer is always better-off by selling her returns as open-box rather than salvaging them.

Proposition 6. *There exists a threshold $\hat{\gamma} = \frac{(2-\beta)\lambda}{\beta}$ for refund sensitivity such that when $\gamma < \hat{\gamma}$ ($\gamma > \hat{\gamma}$), the total market share under a TPPS is greater (less) than the total market share under a SPPS.*

I demonstrate Proposition 6 in Figure 3.3. This figure shows the total market share under both strategies. The top line corresponds to the case of SPPS where total market share is composed solely of new demand. The middle and bottom lines correspond to the cases of TPPS where total market share is compound of new demand and open-box demand for $\gamma > \hat{\gamma}$ and $\gamma < \hat{\gamma}$, respectively. Because customers are heterogenous with respect to their valuations, new demand under the SPPS is always greater than new demand under the TPPS. This implies that open-box products will always cannibalizes new products. Even so, Proposition 6 establishes that, by selling open-box products, the retailer may expand her market share when $\gamma < \hat{\gamma}$. In this case, as illustrated in bottom line of Figure 3.3, the decrease in new demand under the TPPS relative to the SPPS is less than that when $\gamma > \hat{\gamma}$. Besides, when $\gamma < \hat{\gamma}$, some of the customers who do not buy a new product due to high price under a SPPS find open-box products attractive under a TPPS. As a result, the increase in

open-box demand exceeds the decrease in new demand. This, in turn, leads to an overall increase in total market share. When $\gamma > \hat{\gamma}$, the increase in open-box demand does not fully compensate for the decrease in new demand and the retailer loses market share under the TPPS compared to the SPPS.

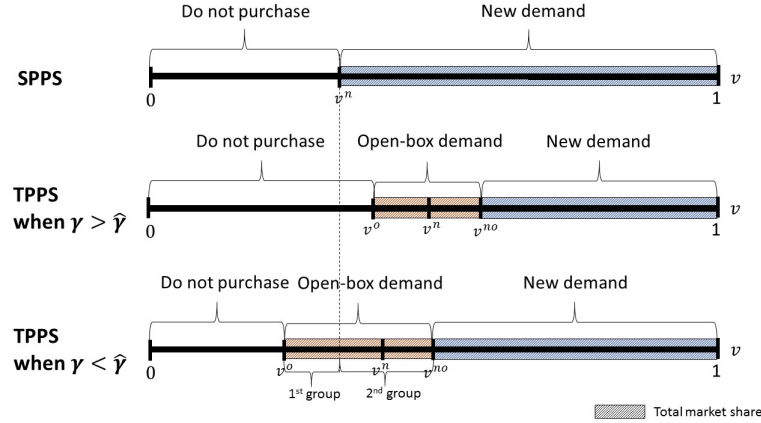


Figure 3.3: Market share change with open-box products

Corollary 2. *The optimal open-box price when $\gamma > \hat{\gamma}$ is greater than the optimal open-box price when $\gamma < \hat{\gamma}$.*

Corollary 2, in conjunction with Proposition 6, establishes that if the TPPS obtains lower market share than the SPPS, the retailer applies a higher open-box price than otherwise. This arises because there are two groups of customers that account for open-box demand as illustrated in Figure 3.3. The first group consists of those who would not buy a new product when that is the only option. The second group consists of those customers who would buy a new product under the SPPS but prefer an open-box product under the TPPS. When $\gamma < \hat{\gamma}$, the former group has lower valuation for open-box product than the later group. This implies, on average, a low willingness-to-pay for open-box products. Accordingly, the open-box price is relatively low. However, when $\gamma > \hat{\gamma}$, the demand for open-box products

comes only from the second group. This implies a higher willingness-to-pay on average for open-box products than when $\gamma < \hat{\gamma}$. Accordingly, the retailer imposes a high price for open-box products.

Proposition 7. *The profit under a TPPS is greater than the profit under a SPPS.*

Proposition 7 establishes that when $\beta > \beta^*$, the TPPS is *always* a profit maximizing strategy for the retailer. When the retailer can increase market share by selling open-box products, it is somewhat intuitive to think that profit will increase as well. However, when the market share change is negative, it is not quite as clear. In short, Corollaries 1 and 2 along with Proposition 6 indicate that when the market share change is negative, the refund amount is lower and the open-box price is higher than those when the market share change is positive. Accordingly, this enables the retailer to compensate for the loss in the market share, resulting in a higher profit under the TPPS relative to that under the SPPS. I believe that the model provides theoretical support for Best Buy's business strategy to sell open-box products side-by-side with new products in its own primary online and physical stores (Seitz, 2013 (accessed May 30, 2014)).

3.4.4 Sensitivity Analysis

In this section, I first provide a sensitivity analysis for the majority of the parameters and decision variables. Later, I present a numerical analysis for the cases in which analytical insights are not tractable. I show that the sensitivity of decision variables with respect to model parameters largely depends on the refund sensitivity γ . I also discuss two counterintuitive results. First, I demonstrate that more product returns do not necessarily lead to a decrease in profit. Second, when the number of open-box products increase due to higher return rates, retailers can increase open-box product price accordingly.

3.4.4.1 Analytical Sensitivity Analysis

Lemma 1. *The change in the optimal decision variables with respect to model parameters is given in Tables 3.3 through 3.5.*

Table 3.3: Sensitivity analysis-1

Optimal solution	Parameter	SPPS		TPPS		γ threshold
		Low γ	High γ	Low γ	High γ	
r^*	p_n	+	+	+	+	
	c	-	-	+	-	$\frac{\beta\lambda}{2-\beta}$
	s	+	+	-	+	$\frac{\lambda[1+\beta\lambda(1-\alpha)]}{1+\lambda(1-\alpha)(2-\beta)}$
	α	+	+	-	+	$\frac{\beta\lambda}{2-\beta}$
p_o^*	p_n			-	-	
	c			-	+	$\tilde{\gamma}$
	s			+	-	$\frac{\lambda[2-\beta+\beta\lambda(1-\alpha)]}{\beta[1+\lambda(1-\alpha)]}$
	α			+	-	$\tilde{\gamma}$

Tables 3.3, 3.4, and 3.5 show, in each row, the change in optimal solutions for each product portfolio strategy as a function of an increase in the value of parameters indicated in the parameter column. For instance, in Table 3.3, an increase in c decreases r^* when the retailer sells only new products. However, when the retailer sells both products, an increase in c increases r^* if γ is lower than the threshold $\frac{\beta\lambda}{2-\beta}$. If $\gamma > \frac{\beta\lambda}{2-\beta}$, an increase in c decreases r^* .

Under the SPPS, r^* decreases with an increase in c and increases with an increase in s and α . These are expected since s and α reduce the retailer's cost from returned products while c increases the cost from them. Accordingly, any increase in s or α (decrease in c) encourages the retailer to offer a more generous refund amount. Under the TPPS, these results hold only when refund sensitivity is high. The reason is that open-box demand is low when γ is high. This implies a low opportunity to reduce the cost of the returns by reselling them. Consequently, the retailer salvages most of open-box products as she does under the SPPS. In this case, the corresponding open-box price increases with an increase (a decrease) in c (s and α) due to the reason explained in Corollary 2. In contrast, when γ is low, the open-box demand is high, implying that the retailer can reduce the product return cost more by reselling open-box products than by salvaging them. This encourages the retailer to increase r^* accordingly with an increase (a decrease) in c (s and α). Consequently, new

demand, therefore, available number of open-box products increases. Hence, the retailer reduces the open-box price to match the supply to demand for open-box products.

Table 3.4: Sensitivity analysis-2

Optimal solution	Parameter	$\gamma < \tilde{\gamma}$	$\gamma > \tilde{\gamma}$
d_n^*, Π^*	p_n	-	+
	c	-	-
	s	+	+
	α	+	+
Q^*	p_n	-	+
	c	-	-
	s	+	+
	α	-	-
d_o^*	p_n	+	-
	c	+	+
	s	-	-
	α	-	-

The sensitivity results in Table 3.4 hold irrespective of the retailer's product portfolio strategy. Any increase in c (decrease in s and α) reduces new demand and increases open-box demand. This results in an overall decrease in profitability. Moreover, Table 3.4 also shows that, order quantity Q and new demand d_n move in the same direction with respect to a change in all model parameters, except α . Since the retailer uses closed-box returns as another source of supply to satisfy the new demand, she can order less new products in the beginning of the season. Conversely, the retailer's profit increases (decreases) with an increase (a decrease) in s and α (c). While the new product price increases the retailer's profit when $\gamma > \tilde{\gamma}$, I observe exactly the opposite when $\gamma < \tilde{\gamma}$. As I discuss in Proposition 2, increasing new product price increases (decreases) new demand when $\gamma > \tilde{\gamma}$ ($\gamma < \tilde{\gamma}$). This, in turn, translates into an increase (decrease) in the retailer's profit.

Table 3.5 shows the sensitivity of the decision variables with respect to λ and γ under the SPSS. When λ increases, the retailer decreases the refund amount to reduce the cost of

Table 3.5: Sensitivity analysis-3 (for the SPPS)

Optimal solution	Parameter	Sensitivity
r^*, d_n^*, Q^*	γ	+
	λ	-
Π^*	γ	+
	λ	+ when $r^* < \alpha c + (1 - \alpha)s$ - when $r^* > \alpha c + (1 - \alpha)s$

returns. Consequently, d_n and Q decrease. Interestingly, I observe that higher returns do not necessarily decrease the retailer's profit. If the optimal refund is less than $\alpha c + (1 - \alpha)s$, an increase in λ increases the profit. The intuition is that if a returned product is open-box, the retailer obtains s by salvaging it. If it is closed-box, she can order one less new product in the beginning of the season, implying a saving of c . Therefore, $\alpha c + (1 - \alpha)s$ can be considered as the expected benefit of a returned product. Hence, when the cost of a returned product is less than its benefit ($r^* < \alpha c + (1 - \alpha)s$), more returns due to an increase in λ increases the profit. Finally, when γ increases, I see that the demand shifts from open-box products to new products. Accordingly, d_n and Q increase, resulting in an increase in profit.

3.4.4.2 Numerical Sensitivity Analysis

The sensitivity of decision variables with respect to λ and γ under the TPPS is not analytically tractable. Instead, I conduct a numerical study over a wide range of model parameter values that correspond to a full factorial design of experiments that consists of 2,187 cases. The model parameters used in the numerical study are presented in Table 3.6.

I find that in most of the cases, the sensitivity of decision variables with respect to λ and γ under the TPPS is the same as that derived analytically for the SPPS. Figure 3.4(a) and Figure 3.5 present two illustrative examples and show the change in decision variables as a function of γ and λ , respectively. I observe that p_o decreases in γ . Moreover, when γ is relatively low, d_o is insensitive to γ . When γ is moderately high, open-box demand slightly increases due to the decrease in p_o . However, if γ is relatively high, customers do not prefer

Table 3.6: Parameters used in the numerical study

Parameter	Values
p_n	$\{0.60, 0.75, 0.90\}$
c	$\{0.20, 0.25, 0.30\}$
s	$\{0.05, 0.10, 0.15\}$
λ	$\{0.10, 0.25, 0.40\}$
γ	$\{0.20, 0.50, 0.80\}$
α	$\{0.20, 0.50, 0.80\}$
β	$\{0.40, 0.60, 0.80\}$

open-box products because returning them is prohibited and thus d_o is lower.

Interestingly, p_o increases in λ . From a supply and demand perspective, one would think that an increase in returns should lead to a decrease in open-box price. However, I observe the opposite. This arises because when λ increases, the refund amount decreases to reduce the cost of returns. Consequently, new demand decreases and open-box demand increases. This encourages the retailer to charge more for open-box products. The retailer is generally worse off with an increase in λ under the TPPS.

I note that while the findings in Figures 3.4(a) and 3.5 hold for a majority cases, there are also a few exceptions. Figure 3.4(b) shows an illustrative example of an exceptional case where the relationship between decision variables and γ is not straightforward and different. The reason is that the range of γ over which the TPPS is feasible is not continuous, implying that new demand and open-box demand may alternately increase and decrease when γ increases. Accordingly, the refund amount and open-box product price have an unpredictable change with an increase in γ .

3.5 Model Extensions

The results of the previous sections regarding the two different product portfolio strategies are obtained under three main assumptions: (1) demands for both products are deterministic, (2) there is no correlation between the two demands, and (3) in case of an inventory shortage, customers do not substitute their first choice with the alternative product. In this

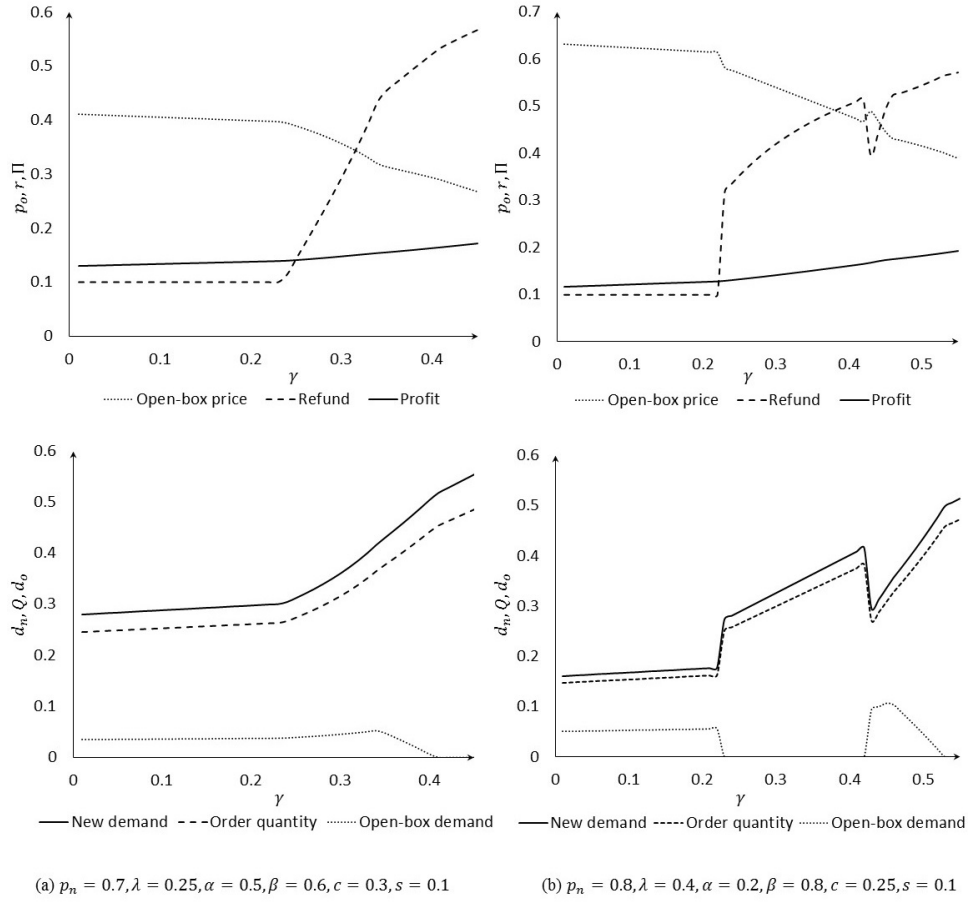


Figure 3.4: The impact of γ on decision variables

section, I relax these assumptions, one at a time, to demonstrate the robustness of the model and the generality of the insights it provides. I show that retailers can use the TPPS to mitigate inventory risk due to the uncertainty in both demands. This advantage of the TPPS is even greater when the random components of both demands are correlated. I also demonstrate that product substitution leads to a further increase in profitability under the TPPS.

3.5.1 Stochastic Demand

To assess the impact of demand uncertainty on the decision variables, I extend the deterministic model by adding random variables. I now define the stochastic demand function for

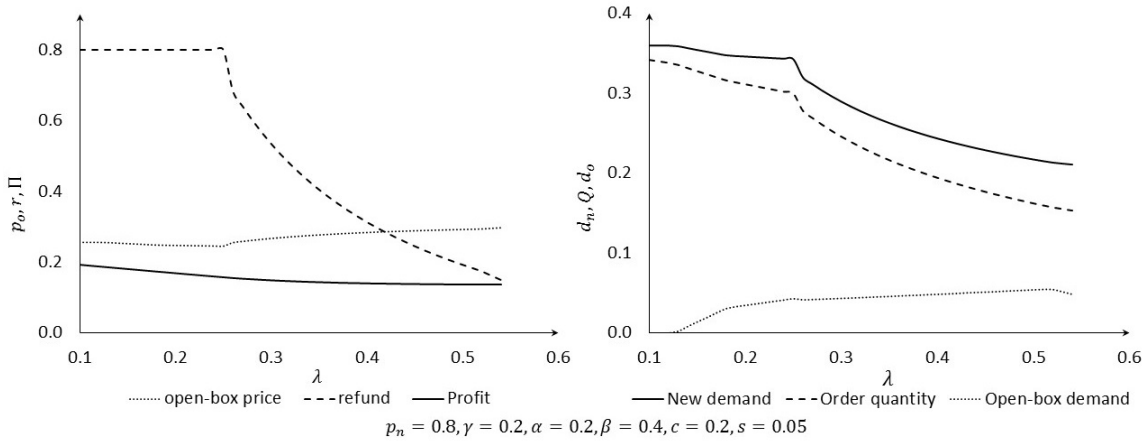


Figure 3.5: The impact of λ on decision variables

new products as $D_n = d_n + \epsilon$ where ϵ is a random variable with a probability density function $f(\cdot)$, a cumulative distribution function $F(\cdot)$, and mean zero. Note that when the retailer orders Q units, due to closed-box returns, the retailer has $\bar{Q} = \frac{Q}{1-\alpha\lambda}$ available new products. Here, \bar{Q} is different from d_n in the deterministic model since new demand is stochastic. For tractability, I assume that open-box demand has two states, a high demand state and a low demand state, and each state is realized with a given probability. This is the approach used in the literature to address uncertainty while maintaining tractability for complex models. Modeling demand in two different periods (Gumus et al., 2013) and modeling two types of customers who differ in their cost of visiting a store (Coughlan and Soberman, 2005) are illustrative examples. For simplicity and without loss of generality, let the open-box demand be \underline{D}_o with a probability of θ or \bar{D}_o with a probability $1 - \theta$, where $(\underline{D}_o + \bar{D}_o)/2 = d_o$, $\underline{D}_o < \min\{\lambda(1 - \alpha)D_n, \lambda(1 - \alpha)\bar{Q}\}$, and $\bar{D}_o > \max\{\lambda(1 - \alpha)D_n, \lambda(1 - \alpha)\bar{Q}\}$. The retailer's expected profit, where the superscript U denotes uncertainty is given by

$$\begin{aligned}
\Pi^U(p_o, r, Q) = & \underbrace{p_n E \min\{D_n, \bar{Q}\}}_{\text{new product sales}} - \underbrace{r \lambda E \min\{D_n, \bar{Q}\}}_{\text{returned}} \\
& + \underbrace{p_o E \min\{\underline{D}_o, (1 - \alpha) \lambda \min\{D_n, \bar{Q}\}\}}_{\text{open-box sales}} + \underbrace{s(\bar{Q} - E \min\{D_n, \bar{Q}\})}_{\text{not sold new}} \\
& \underbrace{s[(1 - \alpha) \lambda E \min\{D_n, \bar{Q}\} - E \min\{\underline{D}_o, (1 - \alpha) \lambda \min\{D_n, \bar{Q}\}\}]}_{\text{not sold open-box}} - cQ
\end{aligned} \tag{3.4}$$

The first term in equation 3.4 corresponds to the revenue from the sales of new products and closed-box returns. The second term indicates the refund amount paid to customers for returned products. The third term corresponds to the revenue from selling open-box products. The fourth and fifth terms show the revenue from salvaging all unsold new and open-box products, respectively. The last term is simply the procurement cost. I assume that any unsatisfied demand is lost. For model simplicity, I assume that a return occurs before an open-box demand so long as the aggregate open-box demand is less than the aggregate number of available returns over the entire selling season.

Proposition 8. 1. The retailer's optimal order quantity (Q^{U*}) and optimal refund amount (r^{U*}) for the SPPS under demand uncertainty is given as

$$\begin{aligned}
Q^{U*} &= Q^* + (1 - \alpha\lambda)F^{-1}\left(\frac{p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)}{p_n - r\lambda - s[1 - \lambda(1 - \alpha)]}\right) \\
r^{U*} &= r^* + \frac{E[D_n - Q^{U*}/(1 - \alpha\lambda)]^+}{2\gamma}
\end{aligned}$$

2. For the TPPS under demand uncertainty, the retailer's optimal order quantity (Q^{U*}) is given as

$$Q^{U*} = Q^* + (1 - \alpha\lambda)F^{-1}\left(\frac{p_n - r\lambda - c(1 - \alpha\lambda)}{p_n - r\lambda - s + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o]}\right)$$

while the optimal refund amount (r^{U*}) and the optimal open-box product price (p_o^{U*}) should satisfy the first order conditions provided in Appendix C.

3. The resulting optimal expected profit is $\Pi^{U*} = \Pi^U(p_o^{U*}, r^{U*}, Q^{U*})$.

In Proposition 8, Q^* and r^* denote the optimal solutions from the deterministic model for a given product portfolio strategy. For the optimal order quantities, the expressions in the inverse of the cumulative distribution function $F^{-1}(\cdot)$ are representative of the critical fractiles of the newsvendor problem for the two strategies. The fractile consists of both

underage cost (i.e. cost the retailer incurs when $D_n > \bar{Q}$) and overage cost (i.e. cost the retailer incurs when $\bar{Q} > D_n$). The numerators represent the underage costs and the denominators represent the summation of underage cost and overage cost. Proposition 8 indicates that, as is typical in a newsvendor problem, the optimal order quantity under uncertainty can be either higher or lower than that without uncertainty, depending on the underage and overage costs. Moreover, to hedge against the risk of demand uncertainty, the retailer offers a higher refund amount under the SPPS than in the deterministic case.

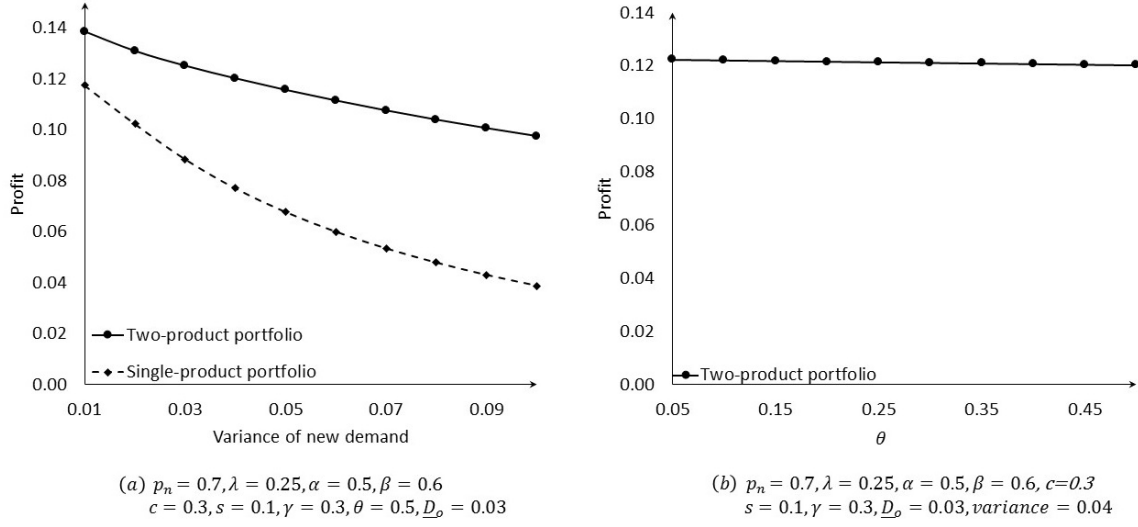


Figure 3.6: The impact of demand uncertainty

I conduct a numerical study by using the parameter values provided in Table 3.6. Two subfigures in Figure 3.6 show the change in profit as a function of demand variability for new demand and open-box demand, respectively. Note that the variability in open-box demand increases with an increase in θ . As expected, an increase in the variability in both demands reduces the profit. Note that the profit loss is less for the TPPS than for the SPPS (Figure 3.6(a)). The reason is that new demand under the TPPS is less than that under the SPPS. Consequently, underage and overage costs, which increase with an increase

in uncertainty, are lower under the TPPS than those under the SPPS. This confirms that the TPPS mitigates inventory risk, implying that retailers facing highly uncertain demand are likely to benefit the most from the TPPS. Further, I observe that although profitability also decreases with respect to an increase in uncertainty in open-box demand, the decrease is trivial since open-box demand relative to new demand is low. Figure 3.6(b) shows an illustrative example for this case.

3.5.2 *Correlated Errors*

In section 3.5.1, I assume that the random components of both demands are not correlated. Due to the model structure, the deterministic components of both demands are implicitly correlated through prices and refund amount. Therefore, I can expect that random components may be either positively or negatively correlated as well. Using the parameters in Table 3.6, I conduct a numerical study to assess the impact of correlated errors of both demands on retailer's profit. Here, I assume that the stochastic demand function for open-box products is $D_o = d_o + \epsilon_o$, where ϵ_o is a random variable with mean zero. Moreover, let ρ denote the correlation between ϵ_n and ϵ_o .

Since the number of available open-box products is a linear function of new demand, it is reasonable to assume that the relationship between random components is also linear. Therefore, I use a bivariate normal distribution in the numerical study. Here ϵ_n and ϵ_o are random variables from a bivariate normal distribution with means zero, standard deviations σ_n and σ_o , and correlation ρ .

Figure 3.7 shows the impact of correlation between ϵ_n and ϵ_o on retailer's profitability under the TPPS. I observe that any increase in the magnitude of correlation between errors, regardless of its sign, increases retailer's profit. This arises because correlation reduces uncertainty in both demands and a decrease in uncertainty leads to an increase in profitability.

Moreover, the profit with a positive correlation is higher than that with a negative correlation when the magnitudes of positive and negative correlations are the same. Since the number of open-box products is a fraction of new demand, positively correlated errors

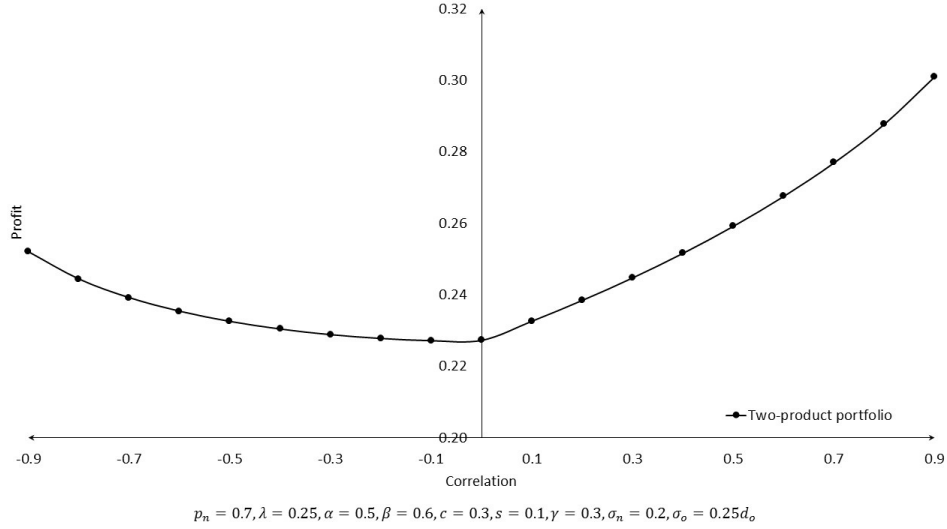


Figure 3.7: The impact of correlation between two demands

result in positively correlated supply and demand for open-box products. This implies low underage and overage costs for open-box demand. In contrast, when errors are negatively correlated, open-box demand will not match to the number of open-box returns. In this case, depending on new demand, the retailer will either have unsold open-box products or not enough open-box products to satisfy the demand. This implies high underage and overage costs. However, the retailer is still better-off with negative correlation than no correlation because the benefit from reduced uncertainty is greater than the cost of a mismatch in supply and demand.

3.5.3 Product Substitution

So far, I have assumed that, under the TPPS customers only buy their first choice and leave without a purchase in case their first choice is not available. However, in practice when their first choice is not available, some customers may prefer to buy the alternative product as long as they have a positive utility for it. This would especially be a concern for the retailer for cases in which the risk of stockout is high and the leftover inventory is costly (e.g. a high value of c and a low value of s). Therefore, in this section I numerically analyze

the impact of substitution on retailer's profit.

Recall that the TPPS is a consideration when $v^{no} > v^n > v^o$. In this case, all customers who prefer a new product (i.e. $1 - v^{no} = d_n$) also have a positive utility for an open-box product. However, only a fraction β of customers who prefer an open-box product have a positive utility for a new product (i.e. $v^{no} - v^n = \beta d_o$). I assume that the probability of substitution between the two products in case the first choice is not available is μ , where $0 \leq \mu \leq 1$. The implicit assumption here is that not all customers necessarily prefer to buy their alternative product in case the first choice is not available. Some of them may go to another retailer to find their first choice.

Under product substitution, the expected number of customers who will substitute a new product with an open-box product is $d^{n \rightarrow o} = \min\{\mu E[D_n - \bar{Q}]^+, E[\lambda(1 - \alpha) \min\{D_n, \bar{Q}\} - \bar{D}_o]^+\}$. Similarly, the expected number of customers who will switch to a new product in case the shortage of open-box products is $d^{o \rightarrow n} = \min\{\mu\beta E[\bar{D}_o - \lambda(1 - \alpha) \min\{D_n, \bar{Q}\}]^+, E[\bar{Q} - D_n]^+\}$. Therefore, the retailer's profit with substitution becomes $\Pi^S = \Pi^U + [p_n - s - (r - s)\lambda]d^{o \rightarrow n} + (p_o - s)d^{n \rightarrow o}$. For convenience, I assume all returns from $d^{o \rightarrow n}$ are simply salvaged. Considering that number of closed-box returns from $d^{o \rightarrow n}$ will be very small, the impact of the assumption of salvaging them on the results is insignificant and it does not change the insights into the problem.

Figure 3.8 shows the impact of product substitution on the retailer's profitability with respect to an increase in new demand uncertainty. New demand uncertainty captures different levels of stockout risk. Note that parameters are selected to illustrate a high cost scenario for leftover inventory. I observe that product substitution mitigates the risk of both overage and underage, resulting in an increase in retailer's profit. Moreover, retailers facing highly demand uncertainty are likely to benefit the most from product substitution under the TPPS. I note that the impact of product substitution on profitability is very low even for a case in which product substitution would be a concern for the retailer. This provides support for the robustness of the model.

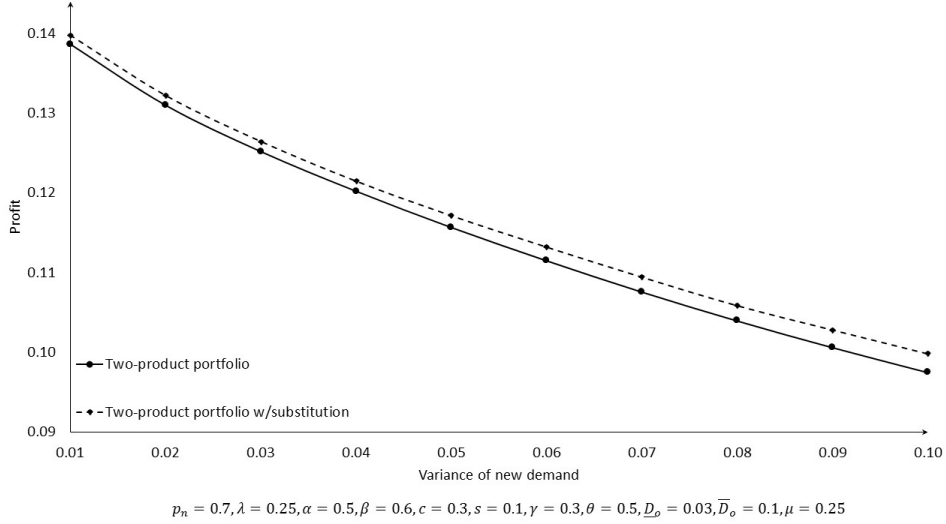


Figure 3.8: The impact of product substitution

3.6 Conclusion

Retailers have developed multiple strategies to effectively manage consumer returns. One of these strategies is to sell returns as open-box products side-by-side with new products at a lower price than the new product price. I observe that many major consumer electronics retailers including Best Buy, Dell, and Amazon.com. follow this strategy, albeit only for certain product categories. Indeed, some other retailers do not even consider this strategy largely due to concerns regarding potential cannibalization of demand for new products.

In this essay, I focus on the retail strategy of selling returns internally and compare it to the strategy of salvaging them. To understand under what conditions retailers prefer one strategy to the other, I develop an analytical model for a retailer that sells a single product under a partial return policy. From a modeling perspective, the contribution of this paper to the literature is three-fold. First, I address the strategy of reselling returns during the selling season when there is imperfect substitution between new and returned products. Second, I distinguish product returns based on their condition (i.e. closed-box vs. open-box) and consider a different reselling option for each condition. Finally, the model captures consumer

behavior of assessing a retailer's return policy before making a purchase decision. The last contribution is specifically important as it leads to very interesting insights for managers. I summarize the key findings and provide a future research direction in the following section.

3.6.1 Managerial Insights and Future Research

The major finding is good news for retailers: the strategy of selling returns as open-box products is *always* more profitable than the strategy of salvaging them as long as there are some customers in the market who find open-box products more attractive than new products. I observe that this result holds even though open-box products cannibalize demand for new products. There are two explanations for the rationale behind this result that depend on the importance of a retailer's return policy on customer's purchase decision. First, when the return policy is not the main determinant for customer's purchase decision, retailers may actually increase their market share by selling returns as open-box. Second, if retailer's return policy is the main determinant for customer's purchase decision, retailers may lose their market share by selling returns as open-box. However, in this case, the refund amount given for product returns is low and the price for open-box products is high compared to the first case. Therefore, regardless of customer's sensitivity to the return policy, in both cases, retailers can overcome the negative effect of cannibalization. This finding supports Best Buy's business strategy of moving all of its open-box products from the secondary market to its main channel as part of its Renew Blue strategy.

A second finding is that, as Nordstrom does, retailers can use a generous return policy to increase demand for new products while charging premium prices. I find that this result holds when customer sensitivity to the retailer's return policy is high. The intuition is that a high price for new products enables retailers to offer a generous return policy through increasing the refund amount. Moreover, demand for new products depends on both price and refund amount. Therefore, when retailer's return policy is the primary determinant for demand, the retailer may attract more customers with a high refund amount than they lose due to a high price.

Next, I find that higher return rates do not necessarily lead to a decrease in profit. The

reason is that a returned product has a value to retailers depending on its condition. If it is a closed-box return, retailers can order one less new product in the beginning of the season since they can sell it as new. This saves them the procurement cost. If it is an open-box return, depending on the strategy they follow, retailers can obtain either a salvage value by salvaging it or a higher margin than the salvage value by selling it as open-box. Overall, if the expected value of a returned product is greater than its cost, which is the refund amount given for it, retailers can actually benefit from higher return rates.

Finally, when product returns increase and consequently the supply for open-box products increases, I establish that retailers do not necessarily need to decrease the price to sell all open-box products. If the refund amount is greater than the potential benefit of a returned product, more returns hurt retailer's profit. A natural mechanism to prevent returns is to restrict return policies by reducing the refund amount. This shifts some of demand from new products to open-box products. Hence, retailers increase the price for open-box products to match demand with supply.

I consider only two strategies for the disposition of consumer returns. Future research may explore other strategies such as sending returns back to manufacturers or selling them in discount outlet stores. Further, the analysis is based on the monopolistic assumption. I do not study how competition from another retailer may change the strategy. The analysis of manufacturer's incentives to encourage the retailer to sell returns as open-box also has potential for future work.

4. SUMMARY AND CONCLUSION

Given that returns in U.S. retailing account for almost 9% of total sales (NRF, 2014), processing returns is now a daily routine for retailers. Practitioners and researchers commonly consider consumer returns a cost center for retailers. Consequently, they mainly focus on preventing returns and minimizing their cost. There are certainly acceptable reasons to consider returns a cost center. Yet, I believe that such a perspective is too limiting since returns also represent an opportunity that can pay dividends beyond their cost when managed effectively.

From a holistic perspective, an effective returns management should (1) start with the in-store shopping experience during a purchase, (2) continue with monitoring and influencing customer satisfaction during a return process, and (3) consider the most effective and efficient disposition methods for returned products after the return process. Drawing upon this holistic approach, my dissertation sheds lights on several issues in effective returns management and provides managerial insights while filling some of the existing gaps in the literature on consumer returns. In particular, this dissertation comprises two essays in which I develop econometric and optimization models to (1) assess the impact of delivering high quality service at the point of purchase on subsequent return behavior, (2) identify the impact of a return event on enhancing customer relationships, and (3) determine the efficiency of a disposition method in which retailers restock their returns as discounted substitutes for new products.

In the first essay, I examine the association between in-store customer shopping experience during a purchase and subsequent return and repurchase behavior. Using over 21 million purchase and return transactions and nearly 75,000 customer satisfaction survey responses from a national jewelry retailer, I conduct a detailed analysis that incorporates a sample selection model with simultaneous recursive equations. The unique and rich data set allows me to tie *customer perceptions* about a purchase experience to the *actual return and*

repurchase behaviors.

In the first part of this essay, I demonstrate that return rates across stores within the same company can vary significantly. Then, I empirically examine this variation with respect to product quality, service quality, and customer satisfaction. Overall, I find that retailers can prevent returns from occurring by influencing customer satisfaction during a purchase event through ensuring high service quality and product quality. The analysis also reveals surprising findings for retailers. For instance, I demonstrate that service quality during a purchase may have a greater influence on returns than product quality. I also show that, in contrast to the common belief that improving salesperson competence eliminates returns, a highly competent salesperson may indeed induce a subsequent return potentially. This can arise if the information the competent salesperson provides unnecessarily increases customer's expectations. Next, I show that a pleasant store environment may also be associated with increased returns. Again, the likely culprit is unmet expectations. After a purchase, products do not necessarily look or function the way that they do in store. Finally, when customers perceive a product's quality as low, they are more likely to return the product even if the actual quality may not be low.

From an effective returns management perspective, the first part of the first essay highlights that retailers may proactively reduce returns even before they arise by delivering a high quality shopping experience during a purchase. Considering that the majority of all returns arise due to a mismatch with customer preferences (Douthit et al., 2011), the findings from this dissertation provide actionable insights for retail managers who seek to prevent consumer returns. On the sales force management side, retailers may design training modules to ensure that salespeople not only successfully sell products, but also set reasonable expectations that actually can be met by the product. On the product side, retailers should emphasize the quality of their products and expose them to a store's product selection during the sales presentation. Finally, on the store environment side, retailers should organize the store environment to set reasonable expectations and not to oversell the product.

In the second part of the first essay, I examine how customer satisfaction influences re-

purchase behavior separately for returners and non-returners. The findings suggest that a return event is likely to increase customer repurchase behavior, on average enhancing revenues by \$171 per year per customer. However, the impact of a return event depends on a customer's satisfaction level during a purchase. For satisfied customers, the event increases preexisting loyalty. For dissatisfied customers, I find that the average spending of customers who do not return the products they purchase after an unsatisfactory experience is only \$6. This implies that dissatisfied customers who do not return their initial purchases are essentially lost. Yet, I demonstrate that when dissatisfied customers return their products, the average spending goes up to \$154. From this perspective, returns from these customers should be encouraged, not prevented. Hence, returns provide an opportunity for retailer to enhance customer relationships that will pay dividends beyond the cost of returns. Accordingly, retailers should actively track customer satisfaction, persuade dissatisfied customers to return their initial purchases, and deliver the same quality level of experience during a return as during a purchase.

Theoretically, the second part of the first essay has two contributions to the academic literature. First, many studies report a positive relationship between customer satisfaction and repurchase behavior (e.g. Cooil et al. (2007); Oliver (2009)). However, some studies empirically show that improvements in customer satisfaction do not always result in higher future purchases (e.g. Van Doorn and Verhoef (2008); Voss et al. (2010)). I contribute to this literature by introducing a return event as another factor that moderates the link between satisfaction and repurchase behavior. Second, the literature on consumer returns examine the impact of returns on loyalty and repurchase behavior for online retailers (Mollenkopf et al., 2007a; Griffis et al., 2012) without considering customer satisfaction with the initial purchase. I contribute to this stream of the literature by explaining how repurchase behavior in physical stores varies with satisfaction for customers who later experience a return relative to those who do not return at all.

In the second essay, I focus on the common retail strategy of selling returns side-by-side with their new products at a discounted price and compare it to the strategy of salvaging

them. The model captures important market characteristics that include consumer choice between new and open-box products, uncertainty and heterogeneity in consumer valuation for both products, and customer sensitivity to a retailer's return policy. The operational decisions of interest are the price of open-box products, the restocking fee for returns, and the order quantity for new product.

I find that, when at least some customers in the market prefer open-box products to new products, selling returns as open-box is always a more profitable strategy than simply salvaging them. This arises even though open-box products cannibalize demand for new products. Furthermore, retailers may increase their overall market share by selling returns as open-box if customers are insensitive to a retailer's return policy. If customers are indeed sensitive, retailers should use a generous policy to increase demand for new products and charge premium prices. I also demonstrate that higher return rates do not necessarily lead to a decrease in profit. Moreover, when product returns increase and consequently the supply for open-box products increases, I establish that retailers do not necessarily need to decrease the price to sell all open-box products.

From an effective returns management perspective, the second essay highlights the importance of return disposition to a retailer's profitability. Retailers typically have concerns about new product cannibalization due to reselling returned products. The second essay establishes that such concerns are generally unwarranted. The findings support many strategies I observe in the marketplace including Best Buy's business strategy of moving all of its open-box products from the secondary market to its main channel and Nordstrom's strategy of using a generous return policy to increase demand for new products while charging premium prices.

From a modeling perspective, the second essay has three contributions to the literature. First, I address the strategy of reselling returns during the selling season when there is imperfect substitution between new and returned products. Second, I distinguish product returns based on their condition (i.e. closed-box vs. open-box) and consider a different reselling option for each condition. Finally, the model captures consumer behavior of assessing

a retailer's return policy before making a purchase decision.

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APPENDIX A

CUSTOMER SATISFACTION SURVEY ITEMS

Product Quality

- (PQ1) Please rate your satisfaction with the overall quality of jewelry/watches at {BrandName}.
 - (PQ2) Please rate your satisfaction with the quality of the jewelry/watch you received for the price you paid.
 - (PQ3) Please rate your satisfaction with the selection of jewelry/watches to meet your needs.
-

Salesperson Competence

- (SC1) Please indicate how much you agree or disagree with the following: The salesperson had significant knowledge of the products they showed me.
 - (SC2) Please indicate how much you agree or disagree with the following: The salesperson was a jewelry/diamond expert.
 - (SC3) Please rate your satisfaction with the salesperson showing you additional items to compliment the primary item you were interested in.
-

Salesperson Helpfulness

- (SH1) Please rate your satisfaction with the friendliness of your salesperson.
 - (SH2) Please rate your satisfaction with the availability of assistance.
 - (SH3) Please rate your satisfaction with the manner in which you were greeted upon entering the store.
-

Store Environment

- (SE1) Please rate your satisfaction with the overall store environment.
 - (SE2) Please indicate how much you agree or disagree with the following: This {BrandName} store has a comfortable environment for me to buy jewelry.
 - (SE3) Please rate your satisfaction with the length of time it took to checkout.
-

Customer Satisfaction

- (CS1) Please rate your overall satisfaction with your experience at this {BrandName}.
- (CS2) Based on this visit, what is the likelihood that you will return to this {BrandName} for your next jewelry/watch purchase.
- (CS3) Based on this visit, what is the likelihood that you will recommend this {BrandName} to others.
-

APPENDIX B

CONFIRMATORY FACTOR ANALYSIS FOR CUSTOMER SATISFACTION SURVEY

Diamond uses Internet-based surveys. While Internet-based survey research has several advantages, careless or inattentive responses are a concern, specifically for data quality. Accordingly, several methods have been suggested to identify careless respondents to increase data quality (Meade and Craig, 2012). Following Meade and Craig (2012), I use the response time (completion time) for each survey response to identify careless responses. The entire survey consists of 48 questions. Descriptive statistics reveal that the average survey response time is 10 minutes and 95% of response times fall in the range of 4-25 minutes. Therefore, I remove survey responses that are completed within less than 4 minutes and more than 25 minutes. This results in 73,598 usable survey responses.

I performed a confirmatory factor analysis (CFA) using Mplus 7 to check how the theoretical model fits the data. Table B.1 presents the CFA results. As seen from the table, the fit statistics for the overall measurement model show acceptable fit (RMSEA=0.057, CFI=0.978, TLI=0.969, SRMR=0.025). Note that for models with large sample sizes, the χ^2 is inflated and always statistically significant (Bentler and Bonnet, 1980; Joreskog and Long, 1993). Therefore, it is not interpretable for model fit for the dataset. However, I use a random sample of 400 survey responses to get an interpretable χ^2 test to assess the model fit for a small sample. The χ^2 (χ^2/df) for the sample data is 139.7 (2.91), indicating a good fit. I also note that the fit indices and factor loadings for the sample data (not shown) are very similar to the fit indices for the entire data.

Following this step, I assess the composite reliabilities as outlined by Fornell and Larcker (1981). The composite reliabilities for all latent variables are greater than the recommended cutoff value of 0.7. In addition, all average variance extracted scores are greater than 0.5, establishing an adequate reliability. I employ Cronbach's alpha to assess scale reliability. Scale reliabilities for all constructs are above 0.7. I assess convergent validity of latent variables

Table B.1: Confirmatory factor analysis results for survey scale development

Latent Variable	Indicator	Standardized Loading	t-values	Cronbach's α
PRODQUAL	PQ1	0.840	519.53	0.834
CR=0.837	PQ2	0.792	421.93	
AVE=0.646	PQ1	0.778	397.41	
COMPETENCE	SC1	0.855	533.28	0.817
CR=0.808	SC2	0.766	375.79	
AVE=0.618	SC3	0.732	326.70	
HELPPFULNESS	SH1	0.802	511.20	0.809
CR=0.885	SH2	0.836	598.88	
AVE=0.699	SH3	0.868	656.61	
ENVIRONMENT	SE1	0.828	574.47	0.819
CR=0.808	SE2	0.790	487.07	
AVE=0.618	SE3	0.737	396.64	
SATISFACTION	CS1	0.582	215.05	0.818
CR=0.821	CS2	0.847	422.82	
AVE=0.634	CS3	0.920	474.30	
- Sample size (n)=73,598. All loadings are significant at $p < 0.001$				
- Goodness-of-Fit Indices: RMSEA=0.057, CFI=0.978, TLI=0.969, SRMR=0.025				
- CR: Construct reliability, AVE: Average variance extracted				
- RMSEA: Root mean square error of approximation, CFI: Confirmatory fit index				
- TLI: Tucker-Lewis index, SRMR: Standardized root mean residual				

by examining the standardized path coefficients from the latent structures to their corresponding manifest indicators (Anderson and Gerbing, 1988). All the path coefficients are greater than 0.40 ($p < 0.001$) and are more than 10 times their standard errors. I assess the discriminant validity between latent variables through the analysis of two-factor CFA model (Bagozzi and Yi, 1988). For each pair of latent constructs, I estimate two models - one constraining the correlation between the pair to unity and one freely estimating the correlation. I use a χ^2 -test to assess if the $\Delta\chi^2$ is significantly lower for the unconstrained models as compared to the constrained model. The $\Delta\chi^2$ exceeds the critical value ($\Delta\chi^2_{\Delta df=1} > 3.84$) for all pairs, establishing discriminant validity. In conclusion, the measures are reliable, valid, and support the theoretical model.

APPENDIX C

PROOFS OF TECHNICAL RESULTS

Proof of Proposition 1:

$$\max \Pi(p_o, r, Q) = \underbrace{p_n d_n}_{\text{new product sales}} - \underbrace{r \lambda d_n}_{\text{returned}} + \underbrace{p_o \min\{d_o, (1-\alpha)\lambda d_n\}}_{\text{open-box sales}} + \underbrace{s[(1-\alpha)\lambda d_n - d_o]^+}_{\text{not sold open-box}} - cQ$$

Case 1: Sell only new products ($d_n > 0$, $d_o = 0$)

Here, $d_n = 1 - p_n + \gamma r$, $d_o = 0$, and $Q = (1 - \alpha\lambda)(1 - p_n + \gamma r)$. The retailer salvages all open-box products. In this case, the profit function becomes $\Pi(r) = [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)](1 - p_n + \gamma r)$. The second derivative of $\Pi(r)$ w.r.t. r is $-2\lambda\gamma < 0$, implying that the profit function is concave. Since the profit function is concave, necessary conditions and sufficient conditions for optimality are that FOC=0. This leads to the optimal refund amount:

$$r^* = \frac{(\lambda + \gamma)p_n - \gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] - \lambda}{2\lambda\gamma}$$

For $d_o = 0$, I should have $p_o = \beta(p_n - \gamma r)$. Plugging r^* into this expression gives the optimal open-box price when the retailer sells only new.

$$p_o^* = \frac{\beta[(\lambda - \gamma)p_n + \gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] + \lambda]}{2\lambda}$$

Case 2: Sell both new and open-box products ($d_n > 0$, $d_o > 0$)

Here, $d_n = 1 - \frac{p_n - p_o - \gamma r}{1 - \beta}$, $d_o = \frac{\beta p_n - p_o - \beta \gamma r}{\beta(1 - \beta)}$, and $Q = (1 - \alpha\lambda)(1 - \frac{p_n - p_o - \gamma r}{1 - \beta})$. If $d_o \geq (1 - \alpha)\lambda d_n$, there is no open-box product to salvage. Otherwise, the retailer salvages all unsold open-box products $[(1 - \alpha)\lambda d_n - d_o]$.

When $d_o < (1 - \alpha)\lambda d_n$, the Hessian is $\begin{pmatrix} \frac{-2\lambda\gamma}{1-\beta} & \frac{-(\lambda+\gamma)}{1-\beta} \\ \frac{-(\lambda+\gamma)}{1-\beta} & \frac{-2}{\beta(1-\beta)} \end{pmatrix}$, whose principal minors $(\frac{-2\lambda\gamma}{1-\beta}, \frac{-2}{\beta(1-\beta)})$ are negative and whose determinant $\frac{4\lambda\gamma - \beta(\lambda+\gamma)^2}{\beta(1-\beta)^2}$ is positive when $\beta < \tilde{\beta} = \frac{4\lambda\gamma}{(\lambda+\gamma)^2}$, implying that the profit function is concave. Setting FOC=0 gives the following expressions for the optimal open-box price and the optimal refund:

$$p_o^* = \frac{\lambda\beta(1-\beta)(\lambda+\gamma) - \beta p_n(\lambda-\gamma)^2 + s\gamma[2\lambda - \beta(\lambda+\gamma)] - \beta\gamma(\lambda-\gamma)[c(1-\alpha\lambda) - s\lambda(1-\alpha)]}{4\lambda\gamma - \beta(\lambda+\gamma)^2}$$

$$r^* = \frac{2(\lambda+\gamma)(1-\beta)p_n - 2\lambda(1-\beta) + s(\gamma-\lambda) - [2\gamma - \beta(\lambda+\gamma)][c(1-\alpha\lambda) - s\lambda(1-\alpha)]}{4\lambda\gamma - \beta(\lambda+\gamma)^2}$$

Proof of Proposition 2:

To prove this proposition, I need to find the expression for the new demand d_n and take the derivative w.r.t. p_n . When I plug r^* and p_o^* into equation 3.1, I find that the optimal new demand is

$$d_n^* = \begin{cases} \frac{\gamma[2p_n(\gamma-\lambda) + s(\lambda+\gamma) + [2\lambda - \beta(\lambda+\gamma)] - 2\gamma[c(1-\alpha\lambda) - s\lambda(1-\alpha)]]}{4\lambda\gamma - \beta(\lambda+\gamma)^2} & \text{if } \underline{\beta} < \beta < \bar{\beta} \\ \frac{p_n(\gamma-\lambda) + \lambda - \gamma[c(1-\alpha\lambda) - s\lambda(1-\alpha)]}{2\lambda} & \text{otherwise} \end{cases}$$

$$\frac{\partial d_n^*}{\partial p_n} = \begin{cases} \frac{2\gamma(\gamma-\lambda)}{4\lambda\gamma - \beta(\lambda+\gamma)^2} & \text{if } \underline{\beta} < \beta < \bar{\beta} \\ \frac{(\gamma-\lambda)}{2\lambda} & \text{otherwise} \end{cases}$$

As seen in both equations, derivatives are positive when $\gamma > \lambda$, implying that new demand increases as p_n increases. When $\gamma < \lambda$, derivatives are negative and therefore new demand decreases in p_n . Here, I assume $\tilde{\gamma} = \lambda$.

Proof of Proposition 3:

$p_n - \gamma r^* > \frac{p_o^*}{\beta}$ requires $\beta p_n(\lambda+\gamma)(\lambda-\gamma) + \lambda\beta(\gamma-\lambda) - 2\lambda\gamma s + \gamma\beta(\lambda+\gamma)[c(1-\alpha\lambda) - s\lambda(1-\alpha)] > 0$ or provides a lower bound for β :

$$\beta^* = \frac{2\lambda\gamma s}{p_n(\lambda^2 - \gamma^2) + \lambda(\gamma - \lambda) + \gamma(\lambda + \gamma)[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]}$$

That is, I have $p_n - \gamma r^* > \frac{p_o^*}{\beta}$, and therefore $d_o > 0$ when $\beta > \beta^*$.

Similarly, when $p_o^* = p_n - \gamma r^* - (1 - \beta)$, the new demand is zero ($d_n = 0$). Plugging r^* and p_o^* into this expression gives the following expression as the upper bound for β under

which I derive the analytical results:

$$\bar{\beta} = \frac{2p_n(\gamma - \lambda) + 2\lambda + s(\lambda + \gamma) - 2\gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]}{\lambda + \gamma}$$

.

Proof of Proposition 4:

To prove this proposition, I need to take the derivative of β^* w.r.t. p_n .

$$\frac{\partial \beta^*}{\partial p_n} = \frac{2s\lambda\gamma(\lambda + \gamma)(\gamma - \lambda)}{[p_n(\gamma - \lambda)(\gamma + \lambda) + \lambda(\lambda - \gamma) - \gamma(\gamma + \lambda)[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]]^2}$$

As seen from the equation, the derivative is positive when $\gamma > \lambda$, implying that β^* increases as p_n increases. When $\gamma < \lambda$, the derivative is negative and therefore β^* decreases in p_n .

If I set $\beta^* = \tilde{\beta}$ and find an equation for p_n (i.e. \hat{p}_n), I can find the value of the new price at which β^* converges to $\tilde{\beta}$.

$$\hat{p}_n = \frac{2\lambda(\gamma - \lambda) - s(\gamma + \lambda)^2 + 2\gamma(\gamma + \lambda)[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]}{2(\gamma^2 - \lambda^2)}$$

Proof of Proposition 5:

To prove this proposition, I simply find the values for p_n that makes r^* equal to p_n and s respectively.

$$r^* = \begin{cases} \frac{2(\lambda + \gamma)(1 - \beta)p_n - 2\lambda(1 - \beta) + s(\gamma - \lambda) - [2\gamma - \beta(\lambda + \gamma)][c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]}{4\lambda\gamma - \beta(\lambda + \gamma)^2} & \text{if } \underline{\beta} < \beta < \bar{\beta} \\ \frac{(\lambda + \gamma)p_n - \gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] - \lambda}{2\lambda\gamma} & \text{otherwise} \end{cases}$$

If $r^* = p_n$, then I find the following expression for $\bar{\bar{p}}_n$.

$$\bar{\bar{p}}_n = \begin{cases} \frac{2\lambda(1-\beta)-s(\gamma-\lambda)+[2\gamma-\beta(\lambda+\gamma)][c(1-\alpha\lambda)-s\lambda(1-\alpha)]}{2(1-\beta)(\lambda+\gamma)-[4\lambda\gamma-\beta(\lambda+\gamma)^2]} & \text{if } \underline{\beta} < \beta < \bar{\beta} \\ \frac{\lambda+\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]}{\lambda+\gamma-2\lambda\gamma} & \text{otherwise} \end{cases}$$

If $r^* = s$, then I find the following expression for \bar{p}_n .

$$\bar{p}_n = \begin{cases} \frac{2\lambda(1-\beta)-s[\gamma-\lambda+\beta(\gamma^2+\alpha\lambda^2)]-\beta\lambda c(1-\alpha\lambda)+(2\gamma-\beta\gamma)[c(1-\alpha\lambda)+s\lambda(1+\alpha)]}{2(\lambda+\gamma)(1-\beta)} & \text{if } \underline{\beta} < \beta < \bar{\beta} \\ \frac{\lambda+\gamma[c(1-\alpha\lambda)+s\lambda(1+\alpha)]}{\lambda+\gamma} & \text{otherwise} \end{cases}$$

Since $\frac{\partial r^*}{\partial p_n}$ is always positive, r^* is an increasing function in p_n . Therefore, the boundary values for p_n are consistent such that $\bar{\bar{p}}_n > \bar{p}_n$.

Proof of Corollary 1:

The difference Θ between the optimal refund when the retailer sells both products and the optimal refund when she sells only new is equal to

$$\Theta = \frac{(\gamma-\lambda)[\beta p_n(\gamma-\lambda)(\gamma+\lambda)-\beta\gamma(\gamma+\lambda)[c(1-\alpha\lambda)-s\lambda(1-\alpha)]-\beta\lambda(\gamma-\lambda)+2\lambda\gamma s]}{2\lambda\gamma[4\lambda\gamma-\beta(\lambda+\gamma)^2]}$$

Using d_o^* from equation 3.2, it is easy to show that $\Theta = -\frac{\beta(\gamma-\lambda)d_o^*}{2\lambda\gamma}$. Since $d_o^* > 0$ when the retailer sells both products, Θ , therefore the change in the refund amount when the retailer starts selling open-box products, is negative when $\gamma > \lambda = \tilde{\gamma}$ and positive when $\gamma < \lambda = \tilde{\gamma}$.

Proof of Proposition 6:

I denote the increase in market size when offering both products as Δ . The increase in market size is simply the difference between the total sales when the retailer sells both products and the total sales when she sells only new products. Hence,

$$\begin{aligned} \Delta &= d_{n-sellboth}^* + d_{o-sellboth}^* - d_{n-sellonlynew}^* \\ \Delta &= \frac{[\beta(\gamma+\lambda)-2\lambda][\beta p_n(\gamma-\lambda)(\gamma+\lambda)-\beta\gamma(\gamma+\lambda)[c(1-\alpha\lambda)-s\lambda(1-\alpha)]-\beta\lambda(\gamma-\lambda)+2\lambda\gamma s]}{2\lambda\beta[4\lambda\gamma-\beta(\lambda+\gamma)^2]} \end{aligned}$$

Using the optimal d_o^* when the retailer sells both products, I can simplify Δ as

$$\Delta = \frac{[2\lambda-\beta(\gamma+\lambda)]d_o^*}{2\lambda}$$

This implies that when $2\lambda - \beta(\gamma + \lambda) > 0$, or when $\gamma < \frac{(2-\beta)\lambda}{\beta}$, Δ is positive. Similarly,

when $\gamma > \frac{(2-\beta)\lambda}{\beta}$, Δ becomes negative, implying a decrease in the market size.

Proof of Corollary 2:

The difference Λ between the optimal open-box price when the retailer sells both products and the optimal open-box price when she sells only new is equal to

$$\Lambda = \frac{[2\lambda - \beta(\gamma + \lambda)][\beta p_n(\gamma - \lambda)(\gamma + \lambda) - \beta\gamma(\gamma + \lambda)[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] - \beta\lambda(\gamma - \lambda) + 2\lambda\gamma s]}{2\lambda[4\lambda\gamma - \beta(\lambda + \gamma)^2]}$$

When I plug r^* and p_o^* in to d_o in equation 3.2, I find the optimal open-box demand when the retailer sells both products.

$$d_o^* = \frac{\beta\gamma(\gamma + \lambda)[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] - \beta p_n(\gamma - \lambda)(\gamma + \lambda) + \beta\lambda(\gamma - \lambda) - 2\lambda\gamma s}{\beta[4\lambda\gamma - \beta(\lambda + \gamma)^2]}$$

Using d_o^* I can show that $\Lambda = -\frac{\beta[2\lambda - \beta(\gamma + \lambda)]d_o^*}{2\lambda}$. Since $d_o^* > 0$ when the retailer sells both products, Λ , therefore the change in the open-box product price when the retailer starts selling open-box products, is positive when $2\lambda - \beta(\gamma + \lambda) < 0$, or when $\gamma > \frac{(2-\beta)\lambda}{\beta} = \hat{\gamma}$. Similarly, when $\gamma < \frac{(2-\beta)\lambda}{\beta} = \hat{\gamma}$, the open-box product price decreases when the retailer starts selling both products. This implies that p_o when $\gamma < \frac{(2-\beta)\lambda}{\beta} = \hat{\gamma}$ is less than p_o when $\gamma > \frac{(2-\beta)\lambda}{\beta} = \hat{\gamma}$.

Proof of Proposition 7:

To find the impact of selling open-box returns on profitability, I compare the profit when the retailer sells both products to the profit when she sells only new products. The change in the profit is equal to

$$\Pi_{sellboth} - \Pi_{sellonlynew} = \frac{[\beta p_n(\gamma - \lambda)(\gamma + \lambda) - \beta\gamma(\gamma + \lambda)[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] - \beta\lambda(\gamma - \lambda) + 2\lambda\gamma s]^2}{4\lambda\gamma\beta[4\lambda\gamma - \beta(\lambda + \gamma)^2]}$$

Using the optimal d_o^* when the retailer sells both products, I can simplify this expression to

$$\Pi_{sellboth} - \Pi_{sellonlynew} = \frac{(d_o^*)^2\beta[4\lambda\gamma - \beta(\lambda + \gamma)^2]}{4\lambda\gamma}$$

Clearly, this expression is strictly positive since $4\lambda\gamma - \beta(\lambda + \gamma)^2 > 0$.

Proof of Lemma 1:

• **Optimal open-box price (p_o^*):**

When the retailer sells both products;

$$\frac{\partial p_o^*}{\partial p_n} = -\frac{\beta(\gamma - \lambda)^2}{4\lambda\gamma - \beta(\gamma + \lambda)^2} < 0$$

$\frac{\partial p_o^*}{\partial c} = \frac{\beta\gamma(\gamma-\lambda)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ is positive when $\gamma > \lambda$ and negative when $\gamma < \lambda$.

$\frac{\partial p_o^*}{\partial s} = \frac{\gamma[\beta\lambda(1-\alpha)(\lambda-\gamma)+2\gamma-\beta(\gamma+\lambda)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ is positive when $\gamma < \frac{\lambda[2-\beta+\beta\lambda(1-\alpha)]}{\beta[1+\lambda(1-\alpha)]}$ and negative when $\gamma > \frac{\lambda[2-\beta+\beta\lambda(1-\alpha)]}{\beta[1+\lambda(1-\alpha)]}$.

$\frac{\partial p_o^*}{\partial \alpha} = \frac{\beta\lambda\gamma(\lambda-\gamma)(c-s)}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ is positive when $\gamma < \lambda$ and negative when $\gamma > \lambda$.

When the retailer sells only new products;

$\frac{\partial p_o^*}{\partial p_n} = \frac{\beta(\lambda-\gamma)}{2\lambda}$ is negative when $\gamma > \lambda$ and positive when $\gamma < \lambda$

$\frac{\partial p_o^*}{\partial c} = \frac{\beta\gamma(1-\alpha\lambda)}{2\lambda} > 0$

$\frac{\partial p_o^*}{\partial s} = -\frac{\beta\gamma(1-\alpha)}{2} < 0$

$\frac{\partial p_o^*}{\partial \alpha} = -\frac{\beta\gamma(c-s)}{2} < 0$

$\frac{\partial p_o^*}{\partial \gamma} = -\frac{\beta[p_n-c+s\lambda+(c-s)\alpha\lambda]}{2\lambda} < 0$

$\frac{\partial p_o^*}{\partial \lambda} = \frac{\beta\gamma(p_n-c)}{2\lambda^2} > 0$

- **Optimal refund amount (r^*):**

When the retailer sells both products;

$\frac{\partial r^*}{\partial p_n} = \frac{2(1-\beta)(\gamma+\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > 0$

$\frac{\partial r^*}{\partial c} = -\frac{(1-\alpha\lambda)[2\gamma-\beta(\gamma+\lambda)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ is positive when $\gamma < \frac{\beta\lambda}{2-\beta}$ and negative when $\gamma > \frac{\beta\lambda}{2-\beta}$

$\frac{\partial r^*}{\partial s} = \frac{(\gamma-\lambda)+\lambda(1-\alpha\lambda)[2\gamma-\beta(\gamma+\lambda)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ is positive when $\gamma > \frac{\lambda[1+\beta\lambda(1-\alpha)]}{1+\lambda(1-\alpha)(2-\beta)}$ and negative when $\gamma < \frac{\lambda[1+\beta\lambda(1-\alpha)]}{1+\lambda(1-\alpha)(2-\beta)}$

$\frac{\partial r^*}{\partial \alpha} = \frac{\lambda(c-s)[2\gamma-\beta(\gamma+\lambda)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ is positive when $\gamma > \frac{\beta\lambda}{2-\beta}$ and negative when $\gamma < \frac{\beta\lambda}{2-\beta}$

When the retailer sells only new products;

$\frac{\partial r^*}{\partial p_n} = \frac{\gamma+\lambda}{2\lambda\gamma} > 0$

$\frac{\partial r^*}{\partial c} = -\frac{(1-\alpha\lambda)}{2\lambda} < 0$

$\frac{\partial r^*}{\partial s} = \frac{1-\alpha}{2} > 0$

$\frac{\partial r^*}{\partial \alpha} = \frac{c-s}{2} > 0$

$\frac{\partial r^*}{\partial \gamma} = \frac{1-p_n}{2\gamma^2} > 0$

$$\frac{\partial r^*}{\partial \lambda} = \frac{c-p_n}{2\lambda^2} < 0$$

• **Optimal new demand (d_n^*):**

When the retailer sells both products;

$$\frac{\partial d_n^*}{\partial p_n} = \frac{2\gamma(\gamma-\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} \text{ is positive when } \gamma > \lambda \text{ and negative when } \gamma < \lambda.$$

$$\frac{\partial d_n^*}{\partial c} = -\frac{2\gamma^2(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} < 0$$

$$\frac{\partial d_n^*}{\partial s} = \frac{\gamma[\gamma+\lambda+2\lambda\gamma(1-\alpha)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > 0$$

$$\frac{\partial d_n^*}{\partial \alpha} = \frac{2\lambda\gamma^2(c-s)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > 0$$

When the retailer sells only new products;

$$\frac{\partial d_n^*}{\partial p_n} = \frac{\gamma-\lambda}{2\lambda} \text{ is negative when } \gamma < \lambda \text{ and positive when } \gamma > \lambda.$$

$$\frac{\partial d_n^*}{\partial c} = -\frac{\gamma(1-\alpha\lambda)}{2\lambda} < 0$$

$$\frac{\partial d_n^*}{\partial s} = \frac{\gamma(1-\alpha)}{2} > 0$$

$$\frac{\partial d_n^*}{\partial \alpha} = \frac{\gamma(c-s)}{2} > 0$$

$$\frac{\partial d_n^*}{\partial \gamma} = \frac{p_n-c+s\lambda+(c-s)\alpha\lambda}{2\lambda} > 0$$

$$\frac{\partial d_n^*}{\partial \lambda} = \frac{\gamma(c-p_n)}{2\lambda^2} < 0$$

• **Optimal order quantity (Q^*):**

When the retailer sells both products;

$$\frac{\partial Q^*}{\partial p_n} = \frac{2\gamma(\gamma-\lambda)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} \text{ is positive when } \gamma > \lambda \text{ and negative when } \gamma < \lambda.$$

$$\frac{\partial Q^*}{\partial c} = -\frac{2\gamma^2(1-\alpha\lambda)^2}{4\lambda\gamma-\beta(\gamma+\lambda)^2} < 0$$

$$\frac{\partial Q^*}{\partial s} = \frac{\gamma(1-\alpha\lambda)[\gamma+\lambda+2\lambda\gamma(1-\alpha)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > 0$$

$$\frac{\partial Q^*}{\partial \alpha} = \frac{\lambda\gamma[\gamma(4c-2p_n-3s+\beta)-\lambda(2-2p_n+s+\beta+2s\gamma+4c\alpha\gamma-4s\alpha\gamma)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2} = -\lambda d_n^* + \frac{2\lambda\gamma^2(c-s)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} \text{ if I use}$$

the expression for the optimal new demand when the retailer sells both products. This

implies that when $d_n^* > \frac{2\gamma^2(c-s)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$, optimal order quantity decreases in α . Since

$$d_n^* = \frac{\gamma^2(2p_n-2c+s-\beta)+\gamma\lambda[2-2p_n-\beta+2c\alpha\gamma+s+2\gamma s(1-\alpha)]}{4\lambda\gamma-\beta(\gamma+\lambda)^2} = \frac{\gamma^2(2p_n-s-\beta)+\gamma\lambda(2-2p_n-\beta+s+2\gamma s)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} +$$

$$\frac{2\gamma^2(c-s)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > \frac{2\gamma^2(c-s)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} \text{ and } \frac{\gamma^2(2p_n-s-\beta)+\gamma\lambda(2-2p_n-\beta+s+2\gamma s)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > 0, \text{ I can prove}$$

that $d_n^* > \frac{2\gamma^2(c-s)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$ always holds, therefore, optimal order quantity decreases in α .

When the retailer sells only new products;

$$\frac{\partial Q^*}{\partial p_n} = \frac{(\gamma-\lambda)(1-\alpha\lambda)}{2\lambda} \text{ is negative when } \gamma < \lambda \text{ and positive when } \gamma > \lambda.$$

$$\frac{\partial Q^*}{\partial c} = -\frac{\gamma(1-\alpha\lambda)^2}{2\lambda} < 0$$

$$\frac{\partial Q^*}{\partial s} = \frac{\gamma(1-\alpha)(1-\alpha\lambda)}{2} > 0$$

$\frac{\partial Q^*}{\partial \alpha} = -\frac{\gamma(p_n-2c+s)-\lambda[p_n-1-2c\alpha\gamma-s\gamma(1-2\alpha)]}{2} = -\lambda d_n^* + \frac{\gamma(c-s)(1-\alpha\lambda)}{2}$ if I use the expression for the optimal new demand when the retailer sells only new product. This implies that when $d_n^* > \frac{\gamma(c-s)(1-\alpha\lambda)}{2\lambda}$, optimal order quantity decreases in α . Since $d_n^* = \frac{\gamma p_n + \lambda - \lambda[p_n - s\gamma(1-\alpha)] - c\gamma(1-\alpha\lambda)}{2\lambda} = \frac{(p_n - \gamma s)(1-\lambda) + \lambda}{2\lambda} + \frac{\gamma(c-s)(1-\alpha\lambda)}{2\lambda} > \frac{\gamma(c-s)(1-\alpha\lambda)}{2\lambda}$ and $\frac{(p_n - \gamma s)(1-\lambda) + \lambda}{2\lambda} > 0$, I can prove that $d_n^* > \frac{\gamma(c-s)(1-\alpha\lambda)}{2\lambda}$ always holds, therefore, optimal order quantity decreases in α .

$$\frac{\partial Q^*}{\partial \gamma} = \frac{(1-\alpha\lambda)[p_n - c + s\lambda(1-\alpha) + c\alpha\lambda]}{2\lambda} > 0$$

$$\frac{\partial Q^*}{\partial \lambda} = -\frac{\gamma(p_n - c) + \alpha\lambda^2[1 - p_n + s\gamma + \alpha\gamma(c-s)]}{2\lambda^2} < 0$$

• **Optimal open-box demand (d_o^*):**

When the retailer sells both products;

$$\frac{\partial d_o^*}{\partial p_n} = \frac{(\lambda-\gamma)(\gamma+\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} \text{ is positive when } \gamma < \lambda \text{ and negative when } \gamma > \lambda.$$

$$\frac{\partial d_o^*}{\partial c} = \frac{\gamma(\gamma+\lambda)(1-\alpha\lambda)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} > 0$$

$$\frac{\partial d_o^*}{\partial s} = -\frac{\gamma\lambda[2+\beta(\lambda+\gamma)(1-\alpha)]}{\beta[4\lambda\gamma-\beta(\gamma+\lambda)^2]} < 0$$

$$\frac{\partial d_o^*}{\partial \alpha} = -\frac{\lambda\gamma(\lambda+\gamma)(c-s)}{4\lambda\gamma-\beta(\gamma+\lambda)^2} < 0$$

• **Optimal profit (Π^*):**

When the retailer sells both products;

$$\frac{\partial \Pi^*}{\partial p_n} = \frac{(\lambda-\gamma)[\gamma(2c-2p_n-s+\beta)+\lambda[-2+2p_n+\beta-2c\alpha\gamma-s[1+2\gamma(1-\alpha)]]]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}. \text{ Using the expression for } Q^*$$

when the retailer sells both products, I can show that $\frac{\partial \Pi^*}{\partial p_n} = \frac{(\gamma-\lambda)Q^*}{\gamma(1-\alpha\lambda)}$. Therefore, $\frac{\partial \Pi^*}{\partial p_n}$ is positive when $\gamma > \lambda$ and negative when $\gamma < \lambda$.

$\frac{\partial \Pi^*}{\partial c} = \frac{\gamma(1-\alpha\lambda)[\gamma(2c-2p_n-s+\beta)+\lambda[-2+2p_n+\beta-2c\alpha\gamma-s[1+2\gamma(1-\alpha)]]]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$. Using the expression for Q^* when the retailer sells both products, I can show that $\frac{\partial \Pi^*}{\partial c} = -Q^*$. Therefore, $\frac{\partial \Pi^*}{\partial c}$ is negative.

$\frac{\partial \Pi^*}{\partial s}$ is trivial. However, using the expression for Q^* when the retailer sells both products, I can show that $\frac{\partial \Pi^*}{\partial s} = \lambda(1-\alpha)d_n^* - d_o^*$. This is positive for the provided solution based on the domain Ω . Therefore, $\frac{\partial \Pi^*}{\partial s}$ is positive.

$\frac{\partial \Pi^*}{\partial \alpha} = \frac{(c-s)\gamma\lambda[\gamma(-2c+2p_n+s-\beta)-\lambda[-2+2p_n+\beta-2c\alpha\gamma-s[1+2\gamma(1-\alpha)]]]}{4\lambda\gamma-\beta(\gamma+\lambda)^2}$. Using the expression for Q^* when the retailer sells both products, I can show that $\frac{\partial \Pi^*}{\partial \alpha} = \frac{\lambda(c-s)Q^*}{(1-\alpha\lambda)}$. Therefore, $\frac{\partial \Pi^*}{\partial \alpha}$ is always positive.

When the retailer sells only new products;

$\frac{\partial \Pi^*}{\partial p_n} = \frac{(\gamma-\lambda)[p_n(\gamma-\lambda)+\lambda-\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]]}{2\lambda\gamma} = \frac{(\gamma-\lambda)Q^*}{\gamma(1-\alpha\lambda)}$. Using the expression for Q^* when the retailer sells only new product. Therefore, $\frac{\partial \Pi^*}{\partial p_n}$ is positive when $\gamma > \lambda$ and negative when $\gamma < \lambda$.

$\frac{\partial \Pi^*}{\partial c} = -\frac{(1-\alpha\lambda)[p_n(\gamma-\lambda)+\lambda-\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]]}{2\lambda} = -Q^*$. Therefore, $\frac{\partial \Pi^*}{\partial c}$ is negative.

$\frac{\partial \Pi^*}{\partial s} = \frac{(1-\alpha)[p_n(\gamma-\lambda)+\lambda-\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]]}{2} = \frac{(1-\alpha)\lambda Q^*}{1-\alpha\lambda}$. Therefore, $\frac{\partial \Pi^*}{\partial s}$ is positive.

$\frac{\partial \Pi^*}{\partial \alpha} = \frac{(c-s)[p_n(\gamma-\lambda)+\lambda-\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]]}{2} = \frac{(c-s)\lambda Q^*}{1-\alpha\lambda}$. Therefore, $\frac{\partial \Pi^*}{\partial \alpha}$ is positive.

$\frac{\partial \Pi^*}{\partial \gamma} = \frac{[(\lambda+\gamma)p_n-\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]]-\lambda[p_n(\gamma-\lambda)+\lambda-\gamma[c(1-\alpha\lambda)-s\lambda(1-\alpha)]]}{4\lambda\gamma^2}$. Using the expressions for the optimal new demand and optimal refund amount when the retailer sells

only new products, I can show that $\frac{\partial \Pi^*}{\partial \gamma} = \frac{\lambda r^* d_n^*}{\gamma} > 0$

$\frac{\partial \Pi^*}{\partial \lambda} = \frac{[1-p_n+s\gamma(1-\alpha)+c\alpha\gamma]^2}{4\gamma} - \frac{\gamma(p_n-c)^2}{4\lambda^2}$. Using the expressions for the optimal new demand and optimal refund amount when the retailer sells only new products, I can show

that $\frac{\partial \Pi^*}{\partial \lambda} = d_n^*(s + \alpha(c-s) - r^*)$. Therefore, when $r^* > s + \alpha(c-s)$, $\frac{\partial \Pi^*}{\partial \lambda}$ is negative.

When $r^* < s + \alpha(c-s)$, $\frac{\partial \Pi^*}{\partial \lambda}$ is positive.

Proof of Proposition 8:

Single-product portfolio strategy solution

In this case, the retailer sells only new products. Therefore, $d_n = 1 - p_n + \gamma r$ and the resulting expected profit function is

$$\Pi^U(r, Q) = \underbrace{p_n E \min\{D_n, \bar{Q}\}}_{\text{new product sales}} - \underbrace{r\lambda E \min\{D_n, \bar{Q}\}}_{\text{returned}} + \underbrace{s\lambda(1 - \alpha) E \min\{D_n, \bar{Q}\}}_{\text{salvaged open-box returns}} + \underbrace{s[\bar{Q} - D_n]^+}_{\text{unsold new}} - cQ$$

I can write the profit function as a piecewise function:

$$\Pi^U(r, Q) = \begin{cases} [p_n - r\lambda + s\lambda(1 - \alpha)]D_n + s(\bar{Q} - D_n) - cQ & \text{if } D_n \leq \bar{Q} \\ [p_n - r\lambda + s\lambda(1 - \alpha)]\bar{Q} - cQ & \text{if } D_n > \bar{Q} \end{cases}$$

Following Petruzzi and Dada (1999), let $z = \bar{Q} - d_n$ and $\epsilon = D_n - d_n$. Then, when I take the expectation, the profit function becomes

$$\begin{aligned} \Pi^U(r, Q) &= \int_{-\infty}^z \{[p_n - r\lambda + s\lambda(1 - \alpha)][d_n + \epsilon] + s(z - \epsilon) - c(1 - \alpha\lambda)(d_n + z)\} f(\epsilon) d\epsilon \\ &\quad + \int_z^{\infty} \{[p_n - r\lambda + s\lambda(1 - \alpha)][d_n + z] - c(1 - \alpha\lambda)(d_n + z)\} f(\epsilon) d\epsilon \end{aligned}$$

Note that $\int_{-\infty}^z (z - \epsilon) f(\epsilon) d\epsilon = \int_{-\infty}^{\bar{Q} - d_n} F(\epsilon) d\epsilon = E[\bar{Q} - D_n]^+$ and can be considered as the probability of overage since I normalize the market size to 1. Similarly, $\int_z^{\infty} (\epsilon - z) f(\epsilon) d\epsilon = \int_{\bar{Q} - d_n}^{\infty} [1 - F(\epsilon)] d\epsilon = E[D_n - \bar{Q}]^+$ and represents the probability of underage.

Finally, note that $\int_{-\infty}^z \epsilon f(\epsilon) d\epsilon + \int_z^{\infty} \epsilon f(\epsilon) d\epsilon = E(\epsilon) = 0$. Therefore, $\int_{-\infty}^z \epsilon f(\epsilon) d\epsilon = -\int_z^{\infty} \epsilon f(\epsilon) d\epsilon$. Now I can write the expected profit function as

$$\begin{aligned} \Pi^U(r, Q) &= [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)]d_n + sE[\bar{Q} - D_n]^+ - [p_n - r\lambda \\ &\quad + s\lambda(1 - \alpha)]E[D_n - \bar{Q}]^+ - c(1 - \alpha\lambda) \int_{-\infty}^z z f(\epsilon) d\epsilon - c(1 - \alpha\lambda) \int_z^{\infty} z f(\epsilon) d\epsilon \end{aligned}$$

Since $c(1 - \alpha\lambda) \int_{-\infty}^z \epsilon f(\epsilon) d\epsilon + c(1 - \alpha\lambda) \int_z^{\infty} \epsilon f(\epsilon) d\epsilon = c(1 - \alpha\lambda)E(\epsilon) = 0$, adding these two terms to the profit function will not change the value of it. Therefore, the profit function becomes

$$\begin{aligned}\Pi^U(r, Q) &= [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)]d_n - [p_n - r\lambda + s\lambda(1 - \alpha) \\ &\quad - c(1 - \alpha\lambda)]E[D_n - \bar{Q}]^+ - [c(1 - \alpha\lambda) - s]E[\bar{Q} - D_n]^+\end{aligned}$$

or

$$\Pi^U(r, Q) = [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)]d_n - C_u E[D_n - \bar{Q}]^+ - C_o E[\bar{Q} - D_n]^+$$

where $C_u = p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)$ is the underage cost and $C_o = c(1 - \alpha\lambda) - s$ is the overage cost.

The first step in maximizing the retailer's profit is to find the optimal \bar{Q} that maximizes the profit function for a given r .

$$\frac{\partial \Pi^U(r, Q)}{\partial \bar{Q}} = C_u - (C_u + C_o)F(\bar{Q} - d_n)$$

Since the second derivative of profit function $[-(C_u + C_o)f(\bar{Q} - d_n)]$ is less than or equal to 0, setting the FOC to 0 gives the optimal order quantity for a given r . Therefore,

$$\bar{Q}^{U*} = F^{-1} \left[\frac{C_u}{C_u + C_o} \right] + d_n$$

The resulting optimal order quantity is $Q^{U*} = (1 - \alpha\lambda) \left[F^{-1} \left[\frac{C_u}{C_u + C_o} \right] + d_n \right]$.

Next, I substitute \bar{Q}^{U*} into the expected profit function. By doing this, I reduce the

bivariate objective function into a univariate function of r as follows:

$$\begin{aligned}\Pi^U(r) &= [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)]d_n - C_u E[D_n - \bar{Q}^{U*}]^+ - C_o E[\bar{Q}^{U*} - D_n]^+ \\ &= [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)]d_n - C_u \int_{\bar{Q}^{U*} - d_n}^{\infty} [1 - F(\epsilon)] d\epsilon \\ &\quad - C_o \int_{-\infty}^{\bar{Q}^{U*} - d_n} F(\epsilon) d\epsilon\end{aligned}$$

$$\begin{aligned}\frac{\partial \Pi^U(r)}{\partial r} &= \gamma[p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)] - \lambda(1 - p_n + \gamma r) \\ &\quad - C_o \cdot F(\bar{Q}^{U*} - d_n) \cdot \left(\frac{\partial \bar{Q}^{U*}}{\partial r} - \gamma\right) + \lambda E[D_n - \bar{Q}^{U*}]^+ \\ &\quad + C_u \cdot [1 - F(\bar{Q}^{U*} - d_n)] \cdot \left(\frac{\partial \bar{Q}^{U*}}{\partial r} - \gamma\right) \\ &= \gamma[p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)] - \lambda(1 - p_n + \gamma r) + \lambda E[D_n - \bar{Q}^{U*}]^+ \\ &\quad - C_o \frac{C_u}{C_u + C_o} \cdot \left(\frac{\partial \bar{Q}^{U*}}{\partial r} - \gamma\right) + C_u \cdot \left[1 - \frac{C_u}{C_u + C_o}\right] \cdot \left(\frac{\partial \bar{Q}^{U*}}{\partial r} - \gamma\right) \\ &= \gamma[p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)] - \lambda(1 - p_n + \gamma r) + \lambda E[D_n - \bar{Q}^{U*}]^+\end{aligned}$$

Since the second derivative of profit function (i.e. $-2\lambda\gamma - \frac{C_o\lambda[c(1-\alpha\lambda)-s]}{(C_u+C_o)f(\bar{Q}^{U*}-d_n)[p_n-r\lambda+s\lambda(1-\alpha)-s]^2}$) is negative, setting the FOC to 0 gives the optimal refund amount (r^{U*}).

$$r^{U*} = \frac{(\lambda + \gamma)p_n - \gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)] - \lambda}{2\lambda\gamma} + \frac{E[D_n - \bar{Q}^{U*}]^+}{2\gamma} \quad (\text{C.1})$$

Two-product portfolio strategy solution

When the retailer sells both new and open-box products, I have four cases: ($D_n \leq \bar{Q}$ and $D_o = \underline{D}_o$), ($D_n \leq \bar{Q}$ and $D_o = \bar{D}_o$), ($D_n > \bar{Q}$ and $D_o = \underline{D}_o$), and ($D_n > \bar{Q}$ and $D_o = \bar{D}_o$). Using the same approach in the previous section, I can rewrite the profit function as:

$$\Pi^U(p_o, r, Q) = \begin{cases} (p_n - r\lambda)D_n - cQ + p_o\underline{D}_o + s[\bar{Q} - D_n + \lambda(1 - \alpha)D_n - \underline{D}_o] & \text{if } D_o = \underline{D}_o \text{ and } D_n \leq \bar{Q} \\ (p_n - r\lambda)D_n - cQ + p_o\lambda(1 - \alpha)D_n + s[\bar{Q} - D_n] & \text{if } D_o = \bar{D}_o \text{ and } D_n \leq \bar{Q} \\ (p_n - r\lambda)\bar{Q} - cQ + p_o\underline{D}_o + s[\lambda(1 - \alpha)\bar{Q} - \underline{D}_o] & \text{if } D_o = \underline{D}_o \text{ and } D_n > \bar{Q} \\ (p_n - r\lambda)\bar{Q} - cQ + p_o\lambda(1 - \alpha)\bar{Q} & \text{if } D_o = \bar{D}_o \text{ and } D_n > \bar{Q} \end{cases}$$

If I use the same transformation I used in the single-product portfolio strategy solution,

I can rewrite the profit function as

$$\begin{aligned}\Pi^U(p_o, r, Q) &= \int_{-\infty}^z \{ (p_n - r\lambda)(d_n + \epsilon) + s(z - \epsilon) - c(1 - \alpha\lambda)(d_n + z) + \theta[p_o \underline{D}_o + s[\lambda(1 - \alpha)(d_n + \epsilon) - \underline{D}_o]] \\ &\quad + (1 - \theta)p_o\lambda(1 - \alpha)(d_n + \epsilon) \} f(\epsilon) d\epsilon + \int_z^\infty \{ [p_n - r\lambda - c(1 - \alpha\lambda)](d_n + z) \\ &\quad + \theta[p_o \underline{D}_o + s[\lambda(1 - \alpha)(d_n + z) - \underline{D}_o]] + (1 - \theta)p_o\lambda(1 - \alpha)(d_n + z) \} f(\epsilon) d\epsilon\end{aligned}$$

When I do the back transformation and write the expected profit as underage and overage costs, I find that

$$\begin{aligned}\Pi^U(p_o, r, Q) &= [p_n - r\lambda + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o] - c(1 - \alpha\lambda)]d_n + \theta \underline{D}_o(p_o - s) \\ &\quad - [p_n - r\lambda - c(1 - \alpha\lambda)]E[D_n - \bar{Q}]^+ \\ &\quad - [c(1 - \alpha\lambda) - s + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o]]E[\bar{Q} - D_n]^+\end{aligned}$$

or

$$\begin{aligned}\Pi^U(p_o, r, Q) &= [p_n - r\lambda + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o] - c(1 - \alpha\lambda)]d_n + \theta \underline{D}_o(p_o - s) \\ &\quad - C_u E[D_n - \bar{Q}]^+ - C_o E[\bar{Q} - D_n]^+\end{aligned}$$

where $C_u = p_n - r\lambda - c(1 - \alpha\lambda)$ is the underage cost and $C_o = c(1 - \alpha\lambda) - s + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o]$ is the overage cost.

The first step in maximizing the retailer's profit is to find the optimal \bar{Q} that maximizes the profit function for a given r and p_o .

$$\frac{\partial \Pi^U(p_o, r, Q)}{\partial \bar{Q}} = C_u - (C_u + C_o)F(\bar{Q} - d_n)$$

Since the second derivative of profit function $[-(C_u + C_o)f(\bar{Q} - d_n)]$ is less than or equal to 0, setting the FOC to 0 gives the optimal order quantity for a given r . Therefore,

$$\bar{Q}^{U*} = F^{-1} \left[\frac{C_u}{C_u + C_o} \right] + d_n$$

The resulting optimal order quantity is $Q^{U*} = (1 - \alpha\lambda) \left[F^{-1} \left[\frac{C_u}{C_u + C_o} \right] + d_n \right]$.

Next, I substitute \bar{Q}^{U*} into the expected profit function.

$$\begin{aligned} \Pi^U(p_o, r) &= [p_n - r\lambda + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o] - c(1 - \alpha\lambda)]d_n + \theta \underline{D}_o(p_o - s) - C_u E[D_n - \bar{Q}^{U*}]^+ - C_o E[\bar{Q}^{U*} - D_n]^+ \\ &= [p_n - r\lambda + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o] - c(1 - \alpha\lambda)]d_n + \theta \underline{D}_o(p_o - s) - C_u \int_{\bar{Q}^{U*} - d_n}^{\infty} [1 - F(\epsilon)] d\epsilon \\ &\quad - C_o \int_{-\infty}^{\bar{Q}^{U*} - d_n} F(\epsilon) d\epsilon \end{aligned}$$

$$\frac{\partial \Pi^U(p_o, r)}{\partial r} = \frac{\gamma}{1 - \beta} [p_n - r\lambda + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o] - c(1 - \alpha\lambda)] - \lambda d_n + \lambda E[D_n - \bar{Q}^{U*}]^+$$

When the second derivative of profit function w.r.t. r (i.e. $-\frac{2\lambda\gamma}{1-\beta} - \frac{\lambda C_o}{C_u + C_o} \left(\frac{\partial \bar{Q}^{U*}}{\partial r} - \frac{\gamma}{1-\beta} \right)$) is negative, setting the FOC to 0 gives the optimal refund amount (r^{U*}). Similarly,

$$\begin{aligned} \frac{\partial \Pi^U(p_o, r)}{\partial p_o} &= \frac{1}{1-\beta} [p_n - r\lambda - c(1 - \alpha\lambda) + \lambda(1 - \alpha)[\theta s + (1 - \theta)p_o]] + \theta \underline{D}_o \\ &\quad + \lambda(1 - \alpha)(1 - \theta)(d_n - E[Q^{U*}/(1 - \alpha\lambda) - D_n]^+) \end{aligned}$$

When the second derivative of $\Pi^U(p_o, r)$ w.r.t. p_o (i.e. $-\frac{2(1-\theta)\lambda(1-\alpha)}{1-\beta} - \frac{(1-\theta)\lambda(1-\alpha)C_u}{C_u + C_o} \left(\frac{\partial \bar{Q}^{U*}}{\partial p_o} - \frac{1}{1-\beta} \right)$) is negative, setting the FOC to 0 gives the optimal open-box price (p_o^{U*}).

APPENDIX D

SOLUTION METHOD FOR NONCONCAVE PROFIT FUNCTIONS

The profit function is not concave either when $d_o > (1 - \alpha)\lambda d_n$ or if $\beta \geq \frac{4\lambda\gamma}{(\lambda+\gamma)^2}$ when $d_o \leq (1 - \alpha)\lambda d_n$. When $d_o > (1 - \alpha)\lambda d_n$, the objective function becomes $\Pi(p_o, r) = [p_n - r\lambda + p_o\lambda(1 - \alpha) - c(1 - \alpha\lambda)](1 - \frac{p_n - p_o - \gamma r}{1 - \beta})$. Since $\Pi(r, p_o)$ is not concave, FOC does not guarantee optimality. However, the second derivative of $\Pi(p_o, r)$ w.r.t. r is $\frac{-2\lambda\gamma}{1 - \beta} < 0$, implying that the profit function is concave in r for any given p_o . Therefore, setting FOC to 0 gives the optimal refund amount for a given p_o .

$$r^*(p_o) = \frac{(\lambda + \gamma)p_n - \lambda[1 - \gamma(1 - \alpha)]p_o - \lambda(1 - \beta) - \gamma c(1 - \alpha\lambda)}{2\lambda\gamma}$$

When $d_o \leq (1 - \alpha)\lambda d_n$, the objective function is $\Pi(p_o, r) = [p_n - r\lambda + s\lambda(1 - \alpha) - c(1 - \alpha\lambda)](1 - \frac{p_n - p_o - \gamma r}{1 - \beta}) + (p_o - s)(\frac{\beta p_n - p_o - \beta \gamma r}{\beta(1 - \beta)})$. Since $\Pi(r, p_o)$ is not concave when $\beta \geq \frac{4\lambda\gamma}{(\lambda+\gamma)^2}$, FOC does not guarantee optimality. However, the second derivative of $\Pi(p_o, r)$ w.r.t. r is $\frac{-2\lambda\gamma}{1 - \beta} < 0$, implying that the profit function is concave in r for any given p_o . Therefore, setting FOC to 0 gives the optimal refund amount for a given p_o .

$$r^*(p_o) = \frac{(\lambda + \gamma)(p_n - p_o) + s\gamma - \lambda(1 - \beta) - \gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]}{2\lambda\gamma}$$

Hence, I can write the optimal refund for a given p_o as a piecewise linear function:

$$r^*(p_o) = \begin{cases} \frac{(\lambda + \gamma)p_n - \lambda[1 - \gamma(1 - \alpha)]p_o - \lambda(1 - \beta) - \gamma c(1 - \alpha\lambda)}{2\lambda\gamma} & \text{if } d_o > (1 - \alpha)\lambda d_n \\ \frac{(\lambda + \gamma)(p_n - p_o) + s\gamma - \lambda(1 - \beta) - \gamma[c(1 - \alpha\lambda) - s\lambda(1 - \alpha)]}{2\lambda\gamma} & \text{if } d_o \leq (1 - \alpha)\lambda d_n \end{cases}$$

By the structure of the model, I have that $p_o > s$. Since $d_o > 0$, I also have $p_n - \gamma r > \frac{p_o}{\beta}$, implying that for the minimum values of γ and r , $p_o < \beta p_n$. Therefore, a one-dimensional

numerical search in p_o using $r^*(p_o)$ in the range of $p_o \in (s, \beta p_n)$ will provide the optimal solutions for the decision variables when they exist. Hence, I can define the optimal solutions for a non-concave profit function as

$$p_o^* = \arg \max_{p_o} \{ \Pi^{DD}(p_o, r^*(p_o), Q) \}$$

$$r^* = r^*(p_o^*)$$